

DEVELOPMENT OF AN EXPERT SYSTEM FOR  
MULTICHANNEL VIB SIGNAL ANALYSIS

BY

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Abstract of Dissertation Presented to the Graduate  
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DEVELOPMENT OF AN EXPERT SYSTEM FOR  
MULTICHANNEL EEG SIGNAL ANALYSIS

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An automated computer analyzing system is designed for multi-channel sleep data analysis. Sleep data are normally analyzed by a human scorer's visual inspection of the record including perception of waveforms and segment-wise classification. A knowledge-based expert system, for data interpretation and classification, is designed on top of an early-processing system in which a heuristic signal processing approach is applied to design narrow waveform recognizers. This is a new approach to the sleep data analysis, providing a different problem solving methodology from analytic signal processing techniques used in conventional approaches. This manuscript also represents a new application of a knowledge-based expert system to an intensive signal processing problem which requires a processing of a large amount of data with an on-line

monitoring feature. The whole idea of this approach is the simulation of the human expert's knowledge. The sleep data analysing problem falls into the category of a knowledge-intensive heuristic problem domain where well-defined algorithms or rules do not exist, but the gestalt perception and heuristic interpretation of a human expert are applied to solve the problem. Large variability of EEG characteristics and the lack of objective EEG models add to the difficulties of analytic signal processing approaches in designing an automated computer analysing system. The expert system technology proposes a different method for problem solving in heuristic domains such as sleep EEG analysis. It also provides a flexible and transparent research environment allowing an easy access and modification of the system knowledge in accordance with frequently varying requirements of the sleep data analysis and its clinical application areas. The developed system shows a man-machine agreement of average 83.6 % with a set of manually selected 14 sample records for subjects 1 to 79 years old. The system performance is discussed with the test result. Problems and limitations for further improvements are also discussed based on the test result.

## CHAPTER I INTRODUCTION

Research investigators have been working for more than 30 years on the development of automated sleep EEG analyzing computer systems [WePS, 1973, 1974, 1975, 1976, 1977, 1978]. Two main objectives are associated with this effort. First, an automated system would provide far more detailed and quantitative descriptions of EEG activities with better accuracy and consistency than a human scorer's visual inspection. The objectivity of the data, which could be obtained from the automated computer analysis, may provide the standard measures to speed up development in the fields of sleep research and clinical applications of EEG [WePS, 1973, 1975, 1976, 1978, 1979, 1980, 1981]. Second, an automated sleep EEG analyzing system would be a great labor saving device. It would replace the human scorer in processing the huge amounts of EEG data involved in the research, thereby saving much of the total expenses of this labor intensive activity.

However, a complete automated sleep EEG analyzing system has not yet been achieved either in terms of satisfactory agreement with human scorers or in terms of practical usefulness of the automated system [WePS, 1973a, 1981]. Automated systems developed so far are incomplete in that they offer only partial solutions to the problem and

are impractical is that they require overly complicated implementation. This is mainly due to both the complex nature of the problem and the lack of knowledge about objective models for EEO waveforms [Mc76, Mc77, Fr77, Is80, Is81, Naf80].

The main aim of this research is to develop an automated sleep EEO analyzing system which performs at a competitive level with a human monitor who visually inspects EEO records. The system design is based upon the idea of simulating the visual inspection and interpretation knowledge of the human experts. This is a new approach to the sleep EEO analysis. A knowledge-based expert system, for the data interpretation and classification, is designed on top of the heuristic signal processing technique which is applied to the early-processing part of the system for the recognition of waveforms. This research also represents a new application of knowledge-based expert system technology to an intensive signal processing problem.

The knowledge-based expert system technology results from the current fundamental shift of interest in the fields of application oriented artificial intelligence [Laff, Gaff, Bell81]. Most of the previous work has been focused on the construction of general-purpose intelligent systems. On the other hand, current emphasis focuses on the construction of an expert system which aims at solving a domain-specific problem with specific and detailed knowledge of a human

expert. The expert system technology can also be regarded as the advent of a newer programming paradigm which is knowledge-based, has an interesting role of machine intelligence, and can utilize the knowledge-base to act in a human-like intelligent manner. The intelligence implied in expert system technology specifies the idea that, the way it solves a problem, the way knowledge is constructed and handled in the system, and the way it interacts with users all should be much the same as those of a human expert. Systems constructed in this way, which are regarded as results of different programming structures in the least sense, are highly flexible and permit a new active user-involving environment. Users can access and modify the knowledge in any range since most of the domain knowledge constructed in this way is transparent to them. The extent of flexibility of the active user involving environment, therefore, is distinguished from that of the limited flexibility of conventional programs where only a certain number of parameters can be interactively adjusted by the user.

The flexibility of the expert system technology depends heavily on the characteristics of a problem domain [Bain, Fe88]. The expert system technology is generally applied to the problem domains which involve extensive, heuristic knowledge, but which lack well defined analytic models to solve the problem [Madd]. The algorithm-based

conventional programming approach cannot provide a suitable way of solving these ill-structured problems of heuristic domain. The flexibility of system operation and the transparency to system's knowledge and its operation are crucial features of the knowledge-based expert system to meet the requirements of an active user involving environment. They allow easy access and modification of the heuristic knowledge which is not inherently static, but changing frequently. Applications of the expert system techniques include medical diagnosis [EXPL, EXPD, EXPH], equipment repair, computer configuration [PCDI], chemical data interpretation and structure identification [SWIN], speech and image understanding [FROLO, HILL], mineral exploration [WATTS], military intelligence and planning [MILP], and other decision-aid problems [WELL]. The sleep EEG/EOG analyzing problem also falls into the category of the problem domain where expert system technology should be applied, since the visual interpretation of the sleep EEG/EOG record stems mainly from the experience-based heuristic knowledge of the human record. However, the knowledge developed in the sleep EEG/EOG analysis is not fixed but can change when new theories are proposed or more experience is acquired. On the other hand, the sleep EEG/EOG analyzing problem differs from those of other expert system domains, in the sense that it involves a large amount of data to be processed and consequently requires the system's processing

and recording efficiency to meet the requirement of an on-line monitoring capability.

Two major tasks involved in the automated sleep EEG analysis are the correct recognition of the specific waveforms in sleep EEG/EOG data and sleep stage scoring based upon the recognized information in the record. The wave activities information and the sleep stage score data can be used in related studies according to the purpose of the research or clinical application.

One of the fundamental difficulties involved in waveform recognition is that there are large inter-subject and intra-subject variabilities in sleep EEG characteristics [Wife]. It is, therefore, difficult to design a robust detection system which works well for a wide range of subjects in the 1 to 75 year age group. Other inherent difficulties include the fact that the straightforward and explicit definitions of the waveforms are not readily available for computer analysis. The waveforms, therefore, are only defined extensively, and the extensive definitions must reflect the large variabilities of the EEG characteristics. Significantly, the variability of the EEG and the lack of good neurophysiological models for EEGs greatly limit the application of analysis signal processing techniques. The automated EEG waveform recognition system cannot rely on conventional signal processing techniques in terms of completeness and practical usefulness of the

system. Thus, waveform recognition eventually comes down to the problem of simulating the human expert's visual inspection by investigating various aspects of EEG characteristics. In this research, the time-domain visual-simulation constitutes the basis for the signal processing methodology. The concept of this signal processing methodology is referred to as the heuristic signal processing technique, in the sense that the EEG is heuristically analyzed applying criteria similar to those of the human expert's visual inspection, but the analysis is not based on an analytic specification of the EEG using conventional signal processing techniques such as spectral analysis, time-domain period-amplitude analysis, and other optimal filtering techniques, etc. [R379, Ref0, J681, M881, G883]. In chapter II, this heuristic approach is further discussed in comparison to other conventional techniques, and system design and implementation are described in detail.

A human expert performs sleep stage scoring by applying a set of predefined sleep staging rules to the observed waveform information [Kasse, Ag72]. However, the sleep staging and data interpretation belong to ill-structured problems in the sense that there do not exist solid algorithmic rules which can provide appropriate solutions to the problem. Rules, if any, are only used as marginal references when the human expert judges each

epoch's stage based on the gestalt observation of the EEO/EOO. The sleep staging system should incorporate the human expert's process of gestalt observation and the heuristic rules for interpretation. These rules are applied differently and change depending on various contexts such as the subject's age, intra-subject EEO characteristics, and the nature of preceding and succeeding adjacent EEO/EOO epochs. The human scorer is adaptive and makes adjustments in applying the scoring rules depending on the various contexts. The lack of well-defined algorithmic rules is the fundamental difficulty in implementing an automated sleep staging system and is one of the significant reasons why the system is implemented in an expert system structure.

Several other important advantages result from implementing the system in an expert system structure. First, without any program modification, rules can be easily changed by the end user, who is most likely a clinician with no programming background, using the knowledge-base editor, which is just a part of the integrated expert system. If the system is implemented in the conventional algorithm-based structure, the end user must go into the program, edit, and recompile through the specific programming language support environment. This means that the sleep stage scoring system cannot be provided as an independent standalone scoring system, but will have to be provided as a part of a whole programming environment or a

specific machine. Second, the user-friendly environment and the transparency of the expert system are very useful features required in a decision-aiding device for the clinical applications [Duffy, Todd, 1984]. For example, "why" and "how" explanation mechanisms and a user-friendly knowledge-base editor can allow easy modification, testing, and evaluation of the system. Third, the operative sleep staging system will be extended in the future for more advanced problems like sleep disorders as other diagnostic problems by incorporating other biological data, such as respiratory data, heart rate, etc. The expert system approach is appropriate for this kind of larger diagnostic problem [Duffy, 1987].

Generally, there does not exist an acceptable standardized expert system structure which works well for all problem domains [Baskin, 1984]. The appropriate system structure should be designed according to the specific nature of the problem domain. The scope of the system development, therefore, includes the development of an expert system shell. The system design emphasizes reasoning and processing efficiency which are important for the system's on-line monitoring capability. The architectural effectiveness of layered structures of data base and knowledge base to handle the different types of knowledge associated with the different processing layers of the EEG analysis, and the effective handling of uncertainties in the

system.

This research is based on the previous achievements which have been obtained through the years of research in the EEG laboratory of the Department of Electrical Engineering at the University of Florida. The SMC (Sleep Analyzing Hybrid Computer) provided the major basis for the development of a waveform recognition system in this research. The SMC was developed by Dr. J.R. Smith through years of research with his colleagues [Smith, Smith, Smith, Smith]. The SMC was designed as an automated sleep EEG analyzing system for the processing of whole night, multi-channel EEG/ECG data. The SMC could detect the predefined waveforms such as alpha, beta, sigma, etc., and also perform the sleep stage scoring. The SMC was a hybrid system consisting of both an analog circuit part and a digital part. The waveform detectors were implemented mainly by analog circuits. The sleep stage scoring and data summarization were performed by a microprocessor-based digital system. The SMC system proved high performance level through verifications by several sleep laboratories, especially in individual waveform detector performance levels.

However, it is necessary to implement an automated system, in a totally digital environment, to overcome certain performance limits and constraints of the hybrid system as a completely automated sleep analyzing machine.

and to provide it in a more compact environment. Especially, under the constraints of the hybrid machine, the detectors of some waveforms, such as the Rapid Eye Movement (REM), the E-complexes, and the Slow Eye Movement (SEM) cannot be efficiently integrated into a single system, because the detection of those waveforms requires intensive use of memory to incorporate multi-channel EEG/EOG information and relatively long segment data information.

A REM wave detection system was developed by Lee [Lee83] in a totally digital environment (VLSI-based microprocessor-based system). The SAC waveform detection scheme was used in the prototype system implementation. A computer language compiler mechanism was used to process token data. Character strings encoded with waveform information were referred to as tokens. The token data were processed by the host computer (Olivetti-4750) for the REM wave detection and minute-summarized wave-activity description generation. The implementation of an expert system for sleep stage scoring and other sleep diagnostic problems, incorporating the minute-summarized wave-activity descriptor information, was proposed speculatively. The compiler generation tools, i.e., lex [Le75] and Yacc were utilized in the implementation of the token processing system. The Yacc was a modified version of YACC [Jo75] by G. Lohrstaedt [Loh8]. The amplitude and period information of all the slow-waves appearing in the EEG/EOG channels needed

to be sent to a host computer for EEM wave detection by further processing. However, there exists a significant restriction in utilizing the computer compiler mechanism for the sleep data analysis. Most of the general parsing rules of the computer language compiler mechanism are too much restrictive to incorporate all the widely varying potential sleep data patterns. The knowledge representation scheme of the system must be in a more flexible form to satisfactorily reflect the visual inspection process for the diverse patterns of the sleep data.

The waveform recognition system, which is the early-processing part of the overall system, is described in chapter II. The general characteristics of sleep EEG, EOG and ECG signals, the signal processing methodology, and the design and implementation of the waveform recognition system are described in detail. In chapter III, expert systems and their applications examples are reviewed with discussions on their limitations and future prospects. Chapter IV describes the knowledge-based signal processing system, which is the second part of the overall system for the sleep EEG signal interpretation and classification. The characteristics of the sleep EEG scoring problem are described first, and then the expert system design considerations are discussed along with the features of its design. The detailed design and implementation of the knowledge-based signal processing system is described according to the major structural

components of the system. The processing results of 24 all night sleep EEG records are presented and discussed in chapter V. Conclusion is presented in chapter VI. Examples of the expert system operation are illustrated with sample screens in appendix A. The system rules implemented in the knowledge base of the system are listed in a tabular form in appendix B. Man-machine agreement tables for each subject record are attached in appendix C.

## CHAPTER 11 WAVEFORM RECOGNITION SYSTEM

This chapter describes the general characteristics of sleep EEG/ECG/EMG, waveform recognition methodologies, and the design and implementation of the waveform recognition system. The waveform recognition system constitutes the early-processing part of the sleep EEG analyzing expert system. It performs assessment and detection of various waveforms in the EEG/ECG/EMG data. The advantages and the fundamental differences of the heuristic approach employed in the design of the waveform recognition system are discussed in comparison to other educational analytic signal processing methodologies applied to the sleep EEG data analysis.

The waveform recognition system is designed and implemented based on a T1900 microprocessor system. The design considerations and the design and implementation details of the early-processing part are described along with all the waveform detectors. Recognized waveform information is encoded in a character string and linked to a host computer for analysis, including sleep stage scoring.

Since the system is ultimately aimed at practical application, the following basic constraints must also be considered in developing the system. The system must be

designed such that it can be implemented on a small portable machine, e.g., a desktop personal computer interfaced with a microprocessor-based analog-processing system. It must be able capable of handling and providing all the EEG/EMG waveform information required by clinicians or researchers, thus resulting in a complete system.

### Sleep EEG, EOG, and EMG

Sleep EEG has been used as one of the most important tools for sleep research and other related clinical applications [BUT, COO, WISE]. It is generally known that the sleep EEG originates from graded synaptic potentials generated by pyramidal cells in the cerebral cortex, which are triggered by rhythmic discharges from the thalamic nuclei. A pacemaker system situated in the thalamus and in the reticular formation probably regulates the synchrony of the cortical signals. The relatively slow time course of excitatory post-synaptic potentials (EPSPs) and inhibitory post-synaptic potentials (IPSPs) corresponds with slow signal and the synchrony is facilitated by the columnar structure of the neurons reaching from upper to lower layers of the cortex [WOLF, MULL, WY4].

Several models have been devised to locate the signal source, to characterize the wave propagation, and to analyze the signal characteristics. Examples of these are: the

current dipole layer model [Häfke] which assumes that the scalp potentials are due to current dipole layers occupying various surface areas of the cortex; a neuronal population model [Chen] which is based on the hypothesis that the surface potentials are a combination of EPSPs and IPSPs which occur both at different depths and different latencies; and autoregressive or other parametric models [Pati, Hsue, Gelfo, Ghil, Iaff] devised for signal processing purposes. However, there is not yet sufficient knowledge about the EEG signal origin and the significance of EEG activities such as the relationships between physiological and clinical states. So, in most cases the EEG signal is presented as a phenomenological model and the signal analysis or visual inspection relies on this EEG model.

The appearance of EEG signals depends on the location of the electrodes on the scalp and on the subject's state of alertness. Therefore, multichannel EEGs should be recorded according to the location dependency of the waveforms of interest. The locations of the electrodes may change and the total number of channels may be reduced according to laboratory practices. But three EEG channels, i.e., frontal (F1-F7), central (C3-A2), and occipital (O3-Oz), are EEG channel (12-21), and one EEG channel according to the 10-20 electrode placement system are recommended for a complete analysis [Jaff, Häfke, Agui]. The system is designed to have the capability for analyzing all three channels.

The frontal channel is recommended for inclusion in the system, since this channel shows clear beta activity such better than any of the other channels investigated. The beta wave activity will be used for a better classification of the REM sleep. The frontal channel also shows a phase-coherent phase relationship with the REM channel better than any of the other REM channels and this relationship will be used in REM, REM, and REM-complexes detection. The central channel shows clear alpha spindles activity better than other channels, and the amplitude level of this channel is relatively higher than other channels. The occipital channel is used mainly for recording the alpha wave activity. This channel could be omitted in the system, since the central channel also shows fairly good alpha wave activity. At least one REM channel is essential for REM, REM, and REM-complexes detection. The main purpose of the REM channel is to complement the capability of the system in separating wake and REM sleep. The REM channel gives information on muscle tension level and this is used to confirm the wake stage, if the muscle tension level is high or to confirm REM sleep, if the muscle tension level is low. This complementary role of REM, the REM wave detector, and the beta waveform detector together will give a very reliable REM sleep separation.

The sleep EEOs of normal subjects show changes of background REM patterns and show appearance of different

waveforms depending on sleep stages. The human scorer visually perceives the appearance of these waveforms and background patterns. He then assigns that segment of the record into one of the stages according to the perceived information. A clear definition of the waveforms in terms of measurable variables is impossible; the waveforms are not analytically measured but directly perceived by the gestalt observation of the scorer. However, tentative descriptions of the waveforms in terms of various grapho-elements are obtained by an intensive observation process of many records for a wide range of subjects.

The waveforms which are used by the human scorer's visual analysis include alpha, beta, delta, sigma, theta, muscle artifact, REM, EEG, k-complexes, and EHG levels. Alpha, beta, sigma, and theta are conveniently classified as episodic indicating that these waveforms are defined as a short burst of periodic waves. The delta is defined in terms of half-wave period and amplitude. The REM, EEG, and k-complexes are defined most importantly in terms of wave shape, background patterns, and time-coherent information of the multichannels, together with the amplitude and the half-wave period. Muscle artifact and EHG are high frequency signals. REM is described as high, low, and medium according to the amplitude levels. Typical REMs for different sleep stages are shown in Fig. 2-1 to Fig. 2-3, and the corresponding EEG waveforms are listed in the

P1 - P7 80S

C1 - C7 80S

O1 - O7 80S

L1 - L7 80S



North Direction



Fig. 2.1. North Arrow (Scale: 1:1000)

17 - 19 000



20 - 22 000



23 - 25 000



26 - 28 000



29 - 31 000



• denotes alpha waveform

Fig. 2.1. Acoustic Signal (Wave Shape 2).

$$C1 = 0.1 \text{ mm}$$

$$C2 = 0.1 \text{ mm}$$

$$C3 = 0.1 \text{ mm}$$

$$C4 = 0.1 \text{ mm}$$

Fig. 2.3. Hinge Design 1

PI - P7 EEG

CI - M7 EEG

CO - COPI EEG

LI - M7 EEG

" stimulus & signal epochs

R-complex

21

Fig. 2.4 Sleep stage 2

F1 - F7 035

C3 - A2 036

C6 - A2 037

A1 - A2 038

6-Comp/Hz

21

Fig. 2.5. Stress Maps 3

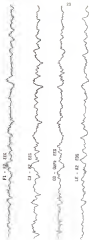


Fig. 2-4. Strip 2-4

EC - E3 100%



CO - A3 100%



CO - A3 100%



EC - E3 100%



Fig. 2.2 Sleep Stage 3 (deep Sleep)

figures. Individual waveform definitions will be described further when the design of each waveform detector is presented.

Sleep stage zero represents the awake state, where the occipital EEG shows the dominance of the alpha activity together with occasional muscle artifacts. The EEG channel often shows the appearance of REM waves which is associated with rapid eye movement [Leiss, 1971]. Sleep stage one usually represents a transition period from the awake state to the sleep state. It is characterized by the disappearance of alpha waves, attenuation of REM amplitude, the absence of distinctive alpha spindle waveforms and h-complexes, and sometimes by the slowly rolling appearance of EEG, which is associated with eye fluttering caused by drowsiness. Sleep stage two is characterized by the appearance of distinctive alpha spindle waveforms and/or the appearance of h-complexes. Sleep stages three and four represent deep sleep periods and are characterized by the occasional appearance of slow, large amplitude waves referred to as delta waves. The REM sleep period is referred to as stage five, which is associated with dreaming. The REM wave shows the appearance of REM waves and/or rolling movements. EEG channels show basically the same appearance as sleep stage one, but a prominent increase in beta activity on the frontal EEG channel is observed during REM periods.

Waveform Detection Methodologies

Various analytic signal processing techniques have been applied to the sleep EEO analysis. These are conveniently divided into two groups, namely, frequency domain analysis and time domain analysis. In frequency domain analysis, spectral parameters are first obtained using one of several spectrum estimation methods, and then various clustering and/or classification algorithms are applied to these spectral parameters for the characterization of the EEO. In time domain analysis, the statistical characteristics of periodicity and amplitude distribution of the EEO are obtained using the time domain waveform descriptors, which are, in each case, period and amplitude.

None of these analytic techniques are complete either in terms of man-machine agreement or in terms of practical usefulness of the system for routine applications. These shortcomings are mainly due to the complex nature of EEO and the lack of knowledge about objective models for EEO waveforms. These limitations impose significant difficulties on the application of an analytic signal processing approach. Thus, satisfactory waveform detection cannot rely on a certain analytic signal processing techniques. However, the analytic quantification of the EEO in terms of statistical variables cannot replace the human scorer's

heuristic quantification which is based on the visual perception of the waveforms in the record.

The heuristic signal processing approach employed in this research emphasizes the correct recognition of all the waveforms of interest in the diagram, instead of trying to characterize the EEG in terms of statistical variables, such as spectral parameters, periodicity, and amplitude distribution as are pursued in other analytic approaches. The recognition is performed by using various grapho-elements and background patterns of the multichannel EEG, ECG, and EMG, similar to the ones the human scorer also uses for the visual perception of the waveforms. The waveforms are extensively defined in terms of these grapho-elements and background patterns for computer analysis.

The discussions of the signal processing techniques are confined to the problem of automated analysis for routine sleep EEG applications. The discussions are mostly focused on the analysis of the background activity and non-stationary activity (or paroxysmal events) aiming at the overall characterization of the sleep EEG. The other problems of EEG analysis such as a spike detection, epilepsy detection, evoked sensory responses, etc., are excluded from the discussion. The advantages and disadvantages of each technique are discussed with respect to the practical usefulness and completeness of the technique for the routine

application of the extended system.

### Spectral Approaches

Spectral analysis is one of the most popular techniques generally applied to EEG analysis. Spectral analysis is based on the underlying assumption that EEG activity may best be quantified by EEG spectral properties. The spectral properties are described in statistical terms based on the assumption of stationary (a few seconds to a few tens of seconds) behavior of the EEG [Ce77, Su73, Joff, Ce76, Su72]. Spectral analysis has become a widely used approach along with the development of analytic signal processing techniques, especially with the advent of the FFT and other fast computational algorithms [Oud5, Oud7, Ye72, Su73, Joff, Joff]. The general approach of these techniques is to first estimate the power spectrum (or some other equivalent of it) of a suitable length of the EEG segment. Each segment of the spectrum data is then further interpreted by applying various clustering and/or classification techniques [Su73a, Joff77, Ce80]. An appropriate power spectrum estimation is therefore the key to this approach. The spectrum estimation techniques have evolved to show several diversities mainly as efforts to achieve better spectrum estimation with higher resolution and less computational complexity. The power spectrum is usually obtained by taking the Fourier transform of the

properly windowed data and squaring its absolute value. The characteristics of the spectrum obtained using this direct method are equivalent to the ones obtained from the periodogram. Several schemes, such as averaging, windowing, overlapping, etc., are developed on an empirical basis to improve the spectrum estimation, though there always exists a trade-off between the resolution of the spectrum estimation and the bias and variance of the estimation [Op93]. The parametric modeling technique, which is relatively recent in modern spectral analysis technology, gives a better spectrum estimation for a shorter data observation and also provides a mathematical model for the signal [Pe71, To75, Mc76, Jaz71, Ch88, Is81]. The model coefficients can be used for the characterization of a segment of the record instead of using the power spectrum parameters.

Spectral analysis can provide an efficient quantification of overall broad-band rhythms present in an EEG epoch since the rhythmic components are relatively enhanced at the corresponding frequency. On the other hand, spectral analysis is not suitable for describing short-term, transient events in the EEG since the transients are smeared in the power spectrum, which is an averaging process over a given time window of the data. To achieve a satisfactory spectral estimate for each sleep staging epoch, a relatively long observation, 30 seconds or more, is required. This

however, is obviously not suitable to describe the non-stationary behavior of EEG activities i.e., short-term, usually less than one second, existing phasic events or paroxysmal events, such as spikes, spindles, K-complexes, or REM waves, cannot be described properly by the power spectrum estimate of a long EEG record.

The parametric modeling technique is used in several recent approaches to improve the resolution in the analysis and to detect transient activities. A quasi-stationary modeling technique with an adaptive segmentation scheme, where the transient behavior of EEG activity is included as a linear superposition on the segment-wise stationary model, is introduced to solve this non-stationary behavior of the EEG [BATT, 1985]. In the study by A. Jahnson [1981], linear model parameters are allowed with time variations to include the transient behavior of EEG activity in the analysis. However, the postulate of linearity between EEG's stationary behavior and non-stationary behavior is very doubtful, because of the observed evidence that the background activity is wiped out by the appearance of a phasic event. It is also hard to verify the validity of the linear model without including higher order correlation terms for the EEG.

Another disadvantage of the spectral analysis method is that the power spectrum is unsuitable for describing the amplitude distribution property of the EEG, especially for

small amplitude EEG waveforms such as beta with a small  $\delta/\beta$  ratio. This is shown well in the study of A. Lubin, L.C. Johnson, and M. Aertio [109], where the sleep stage scoring of human EEG is performed based on the spectral analysis approach. The study reports that the amount of beta activity is minimal in the REM period; however this result is opposite to the visual analysis i.e., the amount of beta activity is far greater in the REM period than in the other REM sleep periods.

None of all, the spectral properties of the EEG obtained through the spectral analysis are not the direct EEG activity interpretation of interest to the clinicians. In, the spectral property data should be interpreted in another domain by using various feature extraction techniques and/or pattern recognition techniques.

Time domain analysis has also been applied as a relatively simple method to quantify the rhythmic properties of the EEG. Basically, the intervals are measured between successive zero-crossing points or peaks where the first derivative of the signal is zero. The distribution of these intervals measure rhythmic activity. The relationships between the period and the amplitude provide various parameters which describe the characteristics of the EEG [110]. A comparison of period-amplitude analysis, utilizing a period and an absolute amplitude histogram, with spectral analysis shows that while the power spectrum

efficiently quantifies the overall power trend in the EEG data, period-amplitude analysis offers more resolution than the power spectrum in detecting details in amplitude and incidence within relatively narrow frequency bands [Roth]. Despite its simplicity and usefulness, this approach has been relatively less attractive to the researchers, mainly because it lacks an analytic tool for signal processing and the method is sensitive to noise and other artifacts [Jaffe]. The autocorrelation and cross-correlation techniques [Jaffe] have also been introduced to analyze the EEG, but with efficient computers available these techniques are now replaced by spectral analysis based on the FFT. Hjorth parameters have been introduced to describe the EEG data quantitatively on the time domain, and these parameters are shown to be equivalent to seventh, second and fourth moments of the normalized power spectral density [Hjorth]. The three parameters used by Hjorth are as follows. The first is called "activity" which is the variance of the amplitude or mean power in the epoch. The second is "mobility" which is the average power of the normalized derivative in the epoch. The third is "complexity" which is the average power of the normalized second derivative in the epoch.

### Statistical Analysis

The recognition of the importance of direct interest to clinicians or sleep researchers is the goal emphasized in

the signal processing approach of this research. This, however, differs from the other analytic signal processing approaches in which the data are quantified in terms of statistical variables. The signal analysis approach is referred to here as "heuristic analysis" in the sense that the waveforms are recognized by mimicking the human scorer's visual perception of the waveforms, i.e., by using various graph-elements and background patterns of the EEG similar to the ones which the human scorer also uses. The signal analysis does not rely on a few limited signal parameters as is the case in period-amplitude analysis, spectral analysis, and parametric modeling approaches. Different sets of various features, including graph-elements, background patterns, and temporal distributions of the multichannel record, should be utilized for recognizing each different waveform.

The sleep EEG analysis problem requires the heuristic approach for the following reasons. The present knowledge about the objective EEG waveform models is not satisfactory, and the variabilities involved in the EEG are too large. Thus, a satisfactory analysis of the EEG cannot rely on one specific analytic signal processing technique. Wide variations in the EEG characteristics are interpreted heuristically by the human scorer, and this capability of interpretation should also be reflected in the signal analysis. However, analytic signal processing techniques

are inherently available to reflect the knowledge factors in the human analysis, since they are based on analytic models of the signal. Because the present knowledge about the EEG and its origins are not yet sufficient to provide objective models for EEG waveforms, it is realistic to rely on subjective models of sleep research and its clinical application areas, i.e., the methodology of EEG analysis based on the visual perception of specific waveforms and the background EEG patterns, rather than to try to provide a new analysis methodology for the clinicians. Most of the analysis signal processing methods emphasize the objectivity of the method and data, and suggest that these data should be utilized in the research and clinical applications instead of visually analyzed data. However, there are significant difficulties in accepting the data provided by the analytic techniques, since reasonable validations of the method and the data, in relation to the neurophysiological models of EEG, cannot be provided for a clinical use. Moreover, the data obtained by the analytic techniques are generally not the sleep information the clinicians use. The best contribution of a computer application for EEG analysis at this stage should be in the replacement of the routine part of the labor intensive sleep analysis in a consistent and objective manner with a technique providing the same kind of information.

Explicit definitions of waveforms in terms of measurable variables are not readily available. The waveforms should be defined objectively in terms of the various morpholements, background patterns, and temporal distribution of the EEG for the heuristic recognition of the waveforms by a computer. Waveform definitions require a process of intensive observation of many records of a wide range of subjects. Since the waveform definitions differ widely from each other, the detailed description of the waveform definitions are given in the individual waveform detector design sections and only brief summaries are shown in Table 3.1.

The waveform Definition criteria include the individual full-cycle wave period window between zero-crossings and peaks, amplitude thresholds, pattern specifications, waveform average period window, half-wave period, wave leading edge slope, background pattern screening, time-coherence of wave shapes in the subthresholds, etc.. All the specifications related to the waveform needs to be incorporated appropriately for correct waveform recognition. The weakness of sensitivity to noise or other artifacts can be avoided by carefully designing the detection to incorporate several aspects of the waveforms, although this weakness can be understood as a by-product paid for by the increase of resolution in describing waveforms on the time domain.



A simple implementation of the signal processing technique is an important aspect to be considered in the system design. The waveform recognition system should be designed to process all the waveforms on a real-time basis by incorporating several functional blocks, such as the A/D conversion unit, the signal conditioning unit, detection unit, multi-channel information processing unit, and data-link unit, etc .

### Waveform Recognition System Design and Implementation

The system, which includes multiple detectors with different detection schemes, is described in the following sequence: first, the functional description of the overall system, second, the design considerations, and third, the individual detector details.

#### Functional Description of the System

The waveform recognition system is implemented on a TI-990S microprocessor-based minicomputer system, which includes a 12 bit A/D converter with two D/A channels, one 16 K-byte RAM board, two serial input-output (I/O) ports, and one parallel input-output (PIO) port.

The functional block diagram of the system is shown in Fig. 2.1. Data from three EBC channels and one ADC channel (or two EBC, one ADC, and one DAC, depending on the

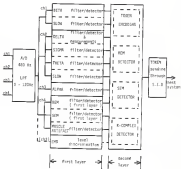


Fig. 2.8: Multi-layered Parallel Processing Architecture of Machine Vision System.

waveform selection) are sampled at 400 Ks per channel and passed through a digital low-pass filter with 100 Ks cutoff frequency. There are two processing layers in the waveform recognition system. The first layer includes the individual waveform detection through the filter/detector unit. The data obtained at the first layer are used for the second layer processing. The second layer processing is performed at a much wider interval of 0.12 second in order to detect certain waveforms, such as the SEP, ION, and X-ray/plasma, which require the information of the other channels and/or the observation of relatively long periods of adjacent SEP/ION background patterns. Also, the information of all the detected waveforms and the delta wave measurements are encoded in a character stream (tokens) and sent to a host computer for further analysis. The processing interval of 0.25 second for the second layer processing is selected by taking into account the following factors: the data compression requirement such that one 5-L/4 inch floppy diskette should be sufficient to accommodate an entire night's four channel token data; the efficiency and time-resolution requirement for the background pattern recognition and the period range of the delta wave.

Since, the single processor (TI-990) system may be capable of processing the multi-tasks for real-time detection of the various waveforms, an appropriate time-multiplexing scheme needs to be designed for the parallel

processing architecture of the waveform detection system. The time-multiplexing scheme of the system is shown in Fig. 2.9. Twelve time-slots consist of one cycle-frame where all the detectors and filters are multiplexed according to their sampling rates as is shown in the figure. Each time-slot, which is  $1/400$  second, contains several detectors and filters which are assigned according to the sampling rates of each filter and detector. Three of the time-slots, as marked in the figure, additionally allocate one of the second layer detectors once every 0.38 second.

The simplified main program flow is depicted in Fig. 2.10. After the initialization of all the buffers, I/O controller, interrupt control registers, and the other I/O ports, the program loops the cycle-frame for the processing. At the end of each time-slot, the interrupt handler routine is triggered by the internal clock. This routine performs the I/O conversion and checks the timer count to service one of the second layer detectors or token decoding routines. The I/O converted data of each channel are low-pass filtered at 100 Hz to remove the high frequency components of the signal above 100 Hz which otherwise may cause aliasing to affect the filters and detectors of the later section. The flow chart of the interrupt handler routine is shown in Fig. 2.11.

The format of token data is shown in Fig. 2.12. Information of all the detected waveforms and delta



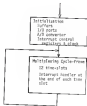


Fig. 2.18 Major Flow Diagram for the Main Routine of a System Subscription System.

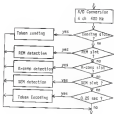


Fig. 2.10 Interrupt Handler Routine Flow Diagram

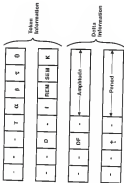


Fig. 2. JOHAN ENCODING

measurement data are encoded into a character string using a signature and bit mapping scheme. Token-encoding routines reads the flag of each waveform detector at every 0.05 second interval and uses two bytes for the encoding of all the flag information. It assigns one (high) to the corresponding bit of the token if the flag of the waveform detector is high, or zero (low) if the flag is low. If a delta wave is detected, then additional two bytes are assigned for the amplitude and period information of the delta wave, respectively. The additional two bytes can be distinguished from the other pair of bytes by the signature bit assigned to the 3rd significant bit of the byte which contains the delta amplitude information. The sign of a delta wave is marked at the 3rd significant bit of the byte which contains the delta period information.

### Design Considerations

Several important design considerations in terms of signal processing aspects, including the selection of A/D conversion unit, the determination of sampling rates for each filter and detector, and the filter characteristics, must be carefully reflected in the system design. The major functional components of the system are the A/D conversion unit, the signal conditioning filters, the individual waveform detectors, and the token encoding and data linking unit.

It has been shown that a 12 bit A/D converter with 65 kHz antialiasing processing is a suitable selection to obtain at least a 40 db S/N ratio [7066].

The A/D conversion sampling rate is one of the important design parameters. The rate must be appropriately determined by considering the overall implementation constraints together with the characteristics of the signal. A higher sampling rate generally brings a higher measurement resolution, but stillface the constraints for the real-time processing of the filters and detectors. The sampling rate on the other hand must be high enough so that the aliasing, possibly caused by the sampling, would minimize distortions in the signal of interest. The A/D conversion rate is 480 Ks in this system for each of the four channels. It is safely assumed that the aliasing contributed by the signal components above 240 Ks ( $1/2 \times 480$  Ks) is negligible. The sampling rate of 480 Ks also gives an appropriate implementation combination with the required sampling rates of the next stage filters and detectors. The digitized data at 480 Ks is first low-pass filtered with a -3 db cut-off frequency at 120 Ks. The digitized low-pass filter is implemented with the transfer function  $H(z) = 0.5 \times (1 - 1/z)$ . The signal components under 120 Ks contain enough information for the waveform detection and analysis purposes of this system, including the detection of the channel artifact and the level discrimination of the DDC. The

avoid artifact and the 120 Hz signal contains the highest frequency components compared to the other waveforms. The signal at the output of this low-pass filter can be further assumed to be band-limited at 120 Hz. Since the power spectrum of the xss itself shows 1/f characteristics, the frequency components above 120 Hz are drastically reduced and are consequently negligible at the filter output. This lowpass filtering allows a lower sampling rate implementation of the later stage filters and detectors, reducing the overall implementation complexity.

Relatively broad-band linear phase FIR (Finite Impulse Response) filters are used for the signal conditioning filters in the system. The broad-band frequency response characteristics are required for the signal conditioning filters, since narrow-band filters may distort the waveforms of interest. The flat pass-band and the sharp cut-off characteristic of the amplitude response are not important for the signal conditioning in this system. The broad-band characteristics and the marginal requirement in pass-band amplitude response and cut-off characteristics of the filter make it feasible to come up with a simplified filter implementation scheme [20b]. The filters designed in this way do not require any multiplications or floating point arithmetic calculations, but can be implemented by shifts and additions. The sampling frequency of an individual signal conditioning

filter is constrained by two factors. The first constraint is the filter order, which increases as the sampling frequency increases when the bandwidth of the filter is fixed, thus increasing the processing time and the filter internal magnifications resulting in the possibility of an overflow. The sampling frequency therefore is limited by the highest feasible order of the FIR filter, which is reported as being around 10th order [P88]. The second constraint is the lowest possible sampling frequency of the filter limited in terms of the Nyquist rate such that the filter sampling frequency must be higher than twice the band-limit of the signal to avoid aliasing.

The period measure between zero-crossing points and/or peaks, which is performed by counting the samples between the two points, is one of the important parameters included in the detector unit. The sampling rate of the detector unit is therefore very important in terms of the measurement resolution. One sample interval is the maximum possible error in determining the period of two points by counting the number of samples. The measurement resolution is readily represented by the following equation.

$$\Delta f = 1/T_s^2 / f_s$$

$1/T_s$  is the period of the two points

$f_s$  is the sampling frequency

$\Delta f$  is the error in frequency.

An example is illustrated with the case of beta. In case of the beta,  $f_0$  is approximately 12 Hz thus  $\Delta f$  is  $\approx 3$  Hz with the sampling frequency  $f_s = 240$  Hz. Increase in the sampling frequency will improve the measurement resolution, but this at the same time decreases the available time-slot; thus, the increase of the sampling frequency cannot be an appropriate solution to improve the resolution. The measurement resolution can be increased also by the interpolation scheme. But the interpolation scheme also brings an increase in the processing time and involves an error of its own. One way, which is used in this system to improve the resolution, is to take the period as the average period of the several adjacent waves. In this way the measurement error is reduced by the factor of the number of the sequences included in the total period as is shown in the following equation.

$$\Delta f = f_0^2 / (N * f_s)$$

### Spindle Detection

The appearance of spindle bursts, such as the alpha spindles, beta spindles, theta spindles, and sigma spindles, is one of the well observed phenomena in human sleep EEG. These waveforms are conventionally grouped as spindles, and their detection schemes are basically similar, although the detailed nature of the waveforms is slightly different for

each.

The first important problem for the correct detection of these waveforms is that these waveforms must be defined explicitly in terms of verifiable measurable by a computer. The waveforms are however heuristically perceived by the human scorer. Thus, straightforward and explicit definitions are not available. Descriptive definitions, which could be obtained by mimicking the human scorer's visual perception reflecting all the various aspects of the EEG, have to be used in the detector design.

A spike is a short burst of waves in sequence that form a waveform giving a distinctive appearance from the background. The spikes are roughly defined by the measure of the periodicity of the individual waves and by the specification to the grouping (bursting) nature of the waveform. These can be further broken down into the following criteria.

- 1 Individual wave period window: zero-crossings  
or peaks
- 2 Individual wave amplitude threshold
- 3 Average period window for the whole sequence of waves is a spike
- 4 Pattern specification for the waveforms

A typical functional block diagram of the spindle detector is shown in Fig. 2.13.

A spindle detector consists of a linear phase FM filter followed by a full-cycle period discriminator, amplitude detector, positive-peak interval discriminator, and pattern recognizer.

Appropriate signal preprocessing is necessary to remove the effects of high frequency noise and of large-amplitude, slow waves. Especially, if a spindle is superimposed on a large-amplitude, slow wave, it is impossible to detect the spindle at the next detector unit by the zero-crossing and peak detection scheme. A relatively broad-band linear phase filter is used for this signal pre-conditioning purpose as explained.

A single spindle is more subject to the effects of large-amplitude, slow waves, because a fair number of edge spindles are superimposed with H-complexes and delta waves. On the other hand, the effect of the large-amplitude, slow waves are less serious for the other spindle waves, such as beta, theta, and alpha, since these other spindles mostly appear on a flat EEG background while the EEG amplitude is relatively small. Thus, the lower edge cutoff characteristic of the edge spindle filter need to have a sharper cutoff characteristic such that the filter successfully removes the effect of large-amplitude, slow wave of the EEG without any significant distortion of the

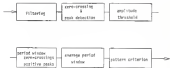


Fig. 8.13 Signal Detector Functional Block Diagram

spindle waveform. The filters for each spindle are connected together with the filters for the other waveforms in Table 2.2.

The signal passed through the conditioning filter is processed at the fast detection unit with various criteria. The frequency of a wave is first defined as the inverse of the full-cycle period which is measured by counting the intervals between adjacent two positive-peaks (or negative-peaks) and/or two positive-going (or negative-going) zero-crossing points. This definition of the frequency is different from that of the sinusoidal wave frequency mostly referred to as a spectral composition of signal in the engineering or scientific sense. However, the definition given here is better justified as more closely mimicking (imitating) the human manner's, since the human motor measures the frequency of a waveform by counting the number of peaks in a specified time window. In the most general sense, the frequency is defined by a human as the number of events occurring per a unit period. The definition as frequency in terms of pure sinusoidal wave is one very specific case of the general definition.

The full-cycle zero-crossing points are first detected by checking the sign change of the samples. Then, each wave's positive-peak is defined by the various sample values between the zero-crossing points. The positive-peak is described by the saved various positive amplitude and the

Table 3.2 Filter Functions

filter	sample frequency (Hz)	pass band	filter transfer function
LPF	200	0 - 10	$H_L(z) = (z^{-1} - 1)^2(z^{-2} + z^{-1} + 1)(z^{-1} + 1)$
	100	0 - 20	$H_L(z) = (z^{-1} - 1)^2 - 1)(z^{-2} + 2.0z^{-1} + 1)(z^{-1} + 1)$
HPF	100	0 - 40	$H_H(z) = (z^{-1} - 1)(z^{-2} + 1)(z^{-1} + 1)(z^{-2} + 1)$
0.5 Hz	10	no filter	$H(z) = (z^{-1} + 1)$
1 Hz	100	10 - 90	$H(z) = (z^{-1} - 1)^2 - 1)(z^{-2} + 0.8z^{-1} + 1)(z^{-1} + 1)(z^{-2} + 1)$
10 Hz	100	0 - 9	$H(z) = (z^{-1} - 1)^2 + 0.7)(z^{-2} + z^{-1} + 1)(z^{-1} + 1)$
HIGHPASS FILTER	200	60 - 100	$H_H(z) = (z^{-1} - 1)$
	100	60 - 100	$H_H(z) = (z^{-1} - 1)$
0.5 Hz	100	0 - 9	$H_H(z) = (z^{-1} - 1)^2 + 0.7)(z^{-2} + z^{-1} + 1)(z^{-1} + 1)$
1 Hz	100	no filter	$H_H(z) = (z^{-1} + 1)$
10 Hz	100	no filter	$H_H(z) = (z^{-1} + 1)$

\* filters are used only for the removal of high end frequency components in the signal.

relative time displacement of the peak from the leading zero-crossing point. The peak has been continuously updated whenever a new sample value is greater than the previous stored peak within the period. If the peak of the full-cycle wave is greater than a certain amplitude threshold, then the periodicity of the individual wave is tested by using corresponding period windows for both intervals between positive-peaks and full-cycle zero-crossing points.

The reliability of the detection generally can be improved by including more measurements in the specification. For instance, the full-cycle zero-crossing period is not sufficient for the spindle wave periodicity measure because the reliability of the detection could be affected by the period measurement error caused by large-amplitude, slow EEO waves, or other noise effects. On the other hand, a spindle's positive-peak interval distribution gives a very good measure to mimic the human observer's visual perception of the spindle. The positive-peak interval is less subject to the large-amplitude, slow waves of the EEO. A positive-peak interval is a measure of the period between the previous wave's peak and the present wave's peak point; the interval is obtained by adding the two intervals, one between the previous wave's peak and the previous wave's ending zero-crossing point, and the other one between present wave's leading zero-crossing point and wave positive-peak.

Thus, if this positive-peak wave interval is not in specified range for a spindle, the previous wave is discarded even though it meets the zero-crossing period and amplitude criteria.

However, the way this system detects and utilizes the information about peaks is distinguished from the generally understood peak detection technique. In general, the peak detection technique looks for the points where the first derivative value of the wave is zero, and applies appropriate period and amplitude criteria on these peaks to analyze waveform characteristics. This approach is taken in the sleep spindle study done by J.O. Principe and J.A. Smith [783]. However, this peak detection technique is more subject to the local variabilities of waves than the zero-crossing technique. On the other hand, in this system, the global wave peak is detected by taking the maximum sample value between zero-crossing points; thus the positive-peak is less subject to local variabilities of the signal.

The positive-peak interval criterion is used together with the zero-crossing period specification for a reliable spindle detection, since the positive-peak interval alone can not impose any restriction on the wave's vertical variation in terms of the vertical asymmetry from the baseline. Also, the two-period-window scheme gives more flexibility in specifying the spindle wave periodicity. The

where allows a looser specification for each period window allowing more variations in terms of each period specification. But, on the other hand, the scheme reflects a tighter specification in terms of the global spindle shape specification by using the two period window.

The human scorer is not very sensitive to the individual wave period and amplitude variations in deriving the spindle. On the other hand, he relies more on the well-shaped global appearance of the whole waveform. The pattern criterion and the average period window are used to specify the global spindle waveform grouping (bureting) nature. The average period window is applied to the total period of several adjacent waves segments in the waveform. The average period window increases the measurement accuracy by a factor equal to the number of waves averaged as is discussed in the previous section. A tighter average period window is applied for the specification of the spindle waveform. On the other hand, the period window for individual waves can become looser to reflect individual wave variations in the spindle. The three numbers in the pattern criteria specify the total number of waves kept in a window, the minimum required number of consecutive in-band waves in the waveform at onset, and the minimum number of the in-band waves to sustain the detection, respectively. The summarized specifications for the spindle waveforms are shown in Table 3.2. The flow chart of the spindle detector

Table 2.1: Summarized specifications for Spindle Waveforms

Criteria spindle	wave period window(ms)		average period window (ms)	amplitude threshold ( $\mu V$ )	pattern criteria
	negative	positive			
Alpha	7.0 - 13.3	7.5 - 12.0	8.8 - 12.0	7.0	4/4/3
Beta	13.0 - 30.0	15.0 - 30.0	20.0 - 30.0	3.0	4/6/3
Gamma	31.0 - 45.1	31.0 - 47.1	31.0 - 40.0	3.0	4/6/3
Delta	5.0 - 9.0	-	5.0 - 9.0	10.0	4/4/3

is shown in Fig. 2.14. This flow chart is applied for all the spindle detectors with appropriate changes in the parameter values according to the criteria of each spindle detector.

### Rapid Eye Movement Detection

The REM wave is detected based on extensive deflections which include the rapidly rising leading edge, quiescent nature of REM activity during REM sleep, and the REM wave amplitude and period window. The rapidly rising REM wave leading edge is used as a distinguishing feature from other REM waves such as delta waves, and REM waves occurring in the EEG channel. It is also necessary to observe the nature of EEG channels' activity during REM sleep to eliminate false REM detections caused by the REM activities appearing on the EEG channel. In particular, the appearance on the EEG channel of large-amplitude EEGs, such as K-complexes or delta waves in REM sleep, may cause false REM detections. This false positive detection has been a problem in accurate REM wave detection using automated computer analysis methods [148]. The EEG during REM sleep is typically represented by the appearance of small-amplitude and high-frequency waves, no delta-like, large-amplitude, slow waves, no rolling movements, thus giving a quiet and flat appearance from the EEG baseline.



The main ideas behind the REM wave detection algorithm of this system is to get a robust REM wave detection by using both the descriptive REM wave criteria and the REM channels' background decreasing with the appropriately chosen time windows. The descriptive REM wave criteria include a slope threshold (500  $\mu\text{V/sec}$ ) on the leading edge, a period window (0.2 - 1.0 sec/half-wave), and a peak amplitude threshold (50  $\mu\text{V}$ ). Two quiescent testing time windows are applied, one each, to the central (CI-AI) and to the frontal (FI-FT) channel REMs as is shown in Fig. 3.18. The central channel time window is applied to the preceding and succeeding two seconds from the terminating edge zero-crossing point of the REM wave. The frontal channel time window is applied to the preceding and succeeding one second from the terminating edge zero-crossing point of the REM wave. The REM wave detection is therefore the following.

• Period: 0.2 - 1.0 sec/half-wave

• Amplitude: 50  $\mu\text{V}$

• Slope: 500  $\mu\text{V/sec}$

• Quiescent test

Frontal channel:  $\pm 1$  sec window, peak

amplitude ratio > 0.5 (between the biggest waves  
in the window)

Central channel:  $\pm 2$  sec window, no delta wave

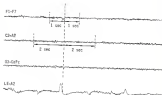


Fig. E.15 Time Windows for IISs Background Pattern Sampling

A two-layered scanning scheme implements the real-time ERM detection algorithm. Each ERM wave is detected at the bottom layer through the filter/detector unit with the descriptive waveforms criteria, and the ERM channels' background scanning is performed at the upper layer with the 0.25 second sampling interval. The functional block diagram of the ERM detection is shown in Fig. 1.18.

The leading edge slope is defined by the line connecting the leading zero-crossing point and the wave peak point of the signal as is shown in Fig. 1.19. In terms of the global description of the ERM wave leading edge, this measurement is found to be a better representation of the edge slope than the measurement where the edge slope is defined as the locally averaged maximum slope value. In terms of accuracy in measuring the edge slope, this global slope measurement is more accurate because the effect of quantization error is greater for the shorter duration measurement. Also in terms of the robustness to the unknown local variability of waves, the global slope measurement is better than locally averaged slope measurement.

To eliminate erroneous effects caused by the ERM baseline movements in measuring the leading slope, a "dead-zone" is first applied to the filtered input signal with an appropriate selection of the dead-zone level. One third of the minimum ERM wave peak threshold, i.e., 20 mv, is



Fig. 3.16 MCR Selector Functional Block Diagram.

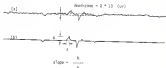


Fig. 2.17 Illustrations of Lead-boosting and Leading Edge Measure PDF wave detection. (a) OSC (LE-42). (b) Extract from the Filter/Lead-boosting unit.

selected as the fixed-zero level, and is found sufficient for the removal of the erroneous effects caused by the EEG baseline movements. This level is not too high for the purpose of an appropriate edge slope representation. To prevent the effect of filter smoothing in measuring the slope, a relatively wide lowpass filter (-3 db at 30 Hz) is used only for the removal of high-end frequency components in the signal [8175].

For the second layer, both the central channel (C3-A2) and the frontal channel (F1-F7) are used to test the EEG's quiescent nature during REM sleep resulting in a higher reliability than testing one EEG channel. A fixed amplitude threshold is used for the C3-A2 channel's quiescent test criterion. On the other hand, the relative peak amplitude ratio between the REM peak and the REM peak is used for the F1-F7 channel's quiescent test. It is observed that the F1-F7 channel often displays the appearance of delta-like waves which actually is caused by eye movement activity. These delta-like waves may give an error in testing the F1-F7 channel's quiescent characterization during REM sleep, although the magnitude level of the delta-like wave at the REM channel is smaller than the REM wave.

It is observed that the frontal(F1-F7) EEG channel shows more REM-related wave channel information than the central (C3-A2) EEG channel. The dominant appearance of

Wave on the frontal channel during REM sleep is not more noticeable than it is on the C3-A2 channel. This is one of the important waveforms which can be utilized, together with the REM wave detection, for the purpose of accurate demarcation of REM sleep periods. It is also observed that the opposite and synchronized phase-amplitude relationship of K-complexes between EOG and EKG channels is more clearly shown on the frontal channel than on the other EEG channels.

The Fig. 2.14 shows the flow chart for the first layer processing of the REM detection. The Fig. 2.15 and 2.20 show the flow charts for the second layer processing of the REM detection.

#### Slow Eye Movement Detection

The slow eye movements (SEM) cause the EOG channel's slow, rolling fluctuations from the baseline. The SEM is physiologically related with the eyes closing, especially during the transition period from wake to sleep caused by drowsiness. The SEM detection scheme includes a half-wave period window, an amplitude threshold, the central SEM channel's background screening, and a wave leading slope threshold. The flow chart for the SEM detection is basically similar to that of REM detector except for the absence of the peak comparison criteria with the other SEM channels.

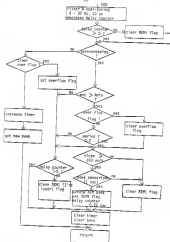


Fig. 2.18 MDX Behavior Flow Chart (First Layer)

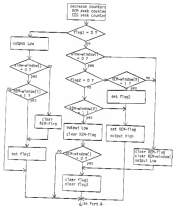


Fig. 3-15 RDP Detector Flow Chart (second layer - part A)

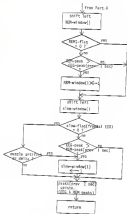


Fig. 2.20 NCH Detector Flow Chart (second Type - part B)

### K-complexes Detection

The main usage of the K-complexes detector in the present system has twofold, to gain better confidence in scoring sleep stage two by complementing the apnea detector information, and to accurately demarcate the sleep stages two and three. The K-complexes detector uses an algorithm structure similar to that of the REM wave detector, since the detection of the K-complexes also requires the same-channel information such as the synchronization of peaks, the opposite phasic relationship between EEOs and EOG, and a quiescent criterion.

Presently, synchronization of EEOs and EOG is detected with a time window, i.e., 0.75 second, across the EEO and EOG channels (specifically F1-F7, C1-A2, and EEO). The amplitude threshold (80  $\mu$ v) and the relatively longer period threshold (0.3 - 1.8 sec/half-wave) are used as the K-complexes criteria. The current definition of K-complexes in the algorithm requires no delta-like slow and large-amplitude wave within the interval of preceding and succeeding two seconds from the K-complexes, since the present K-complexes detection algorithm is less reliable in sleep stages three and four. Therefore, the K-complexes information in these sleep stages is not utilized in the sleep scoring process.

The more descriptive K-complexes detection criteria, such as the opposite phasic relationship between the same

EEG channels and the EOG channel, upward going characteristics, and slope criterion should be utilized for a better E-complex detection.

#### Delta Wave Detection and Measurement

The delta detector is implemented with a period window (0.25 - 1.0 sec/half-wave) and a relatively low amplitude threshold of 14.7  $\mu$ v. The amplitude and period values of each delta wave are sent to the host computer through a serial port for a post delta processing. The post delta processing is necessary for an accurate delta summary because the variations of the EEG amplitude level provide good delta wave detections if the same amplitude threshold is used for all subjects. Individual delta wave amplitude and period are necessary also for the purpose of more quantitative delta studies.

The delta amplitude is quantized into 16 levels from 14.7  $\mu$ v to 100  $\mu$ v with the 5.2  $\mu$ v resolution and the period is also quantized into 16 levels from 0.25 to 1.0 second with the 47 msec resolution.

#### Muscle Artifact and EMG Analysis

Muscle artifact is associated with the movement of body. The signal consists of high frequency components usually above 10 Hz. The detector consists of a highpass filter, a zero-crossing detector, an amplitude threshold (10

uv), a full-cycle period discriminator (24.3  $\pm$  1.0 Hz), an average period window, a 40 Hz notch filter, and a pattern specification (4/8/3). The flow chart of the muscle artifact detector is same as that of the spindle detector as is shown in Fig. 2.14, except for the addition of 40 Hz notch filter. The 40 Hz notch filter is operated in conjunction with the average period window. The purpose of this filter is to reduce the effects of 40 Hz environmental noise in detecting muscle artifact.

The EMG signal amplitude is described into three levels, i.e., below 10  $\mu$ v, between 10  $\mu$ v and 20  $\mu$ v, and above 20  $\mu$ v. The EMG discriminator structure is same as the muscle artifact detector but three different amplitude thresholds are applied for the EMG level discrimination.

## CHAPTER 111 SURVEY ON EXPERT SYSTEMS AND THEIR APPLICATIONS

In this chapter, general aspects of expert systems are briefly reviewed with explanations on their historical background, distinguishing features from algorithm-based programs, and architectural aspects. Several expert system application examples are then briefly reviewed with an emphasis on a critical view of the expert system approach, discussing their limitations and future prospects in relation to their application domain characteristics.

### Expert System Overview

Knowledge-based expert systems have been drawing considerable interest in the application-oriented artificial intelligence (AI) field since the mid-1970s. This area of AI has concentrated on the construction of a high-performance system which simulates tasks at the level of a human expert in a specialized professional domain. Historically, the knowledge-based expert system is a fundamental shift in the application-oriented AI area from the earlier effort to find general methods for problem-solving and use them to create general purpose programs. This strategy to achieve a general problem

solver. Despite some interesting progress, has produced no significant advances because developing general-purpose programs has been too difficult and ultimately fruitless; the main emphasis has shifted to the knowledge involved in a problem domain. Researchers have pointed out that the problem-solving power of a program comes from the knowledge it possesses, not just from the formalism and inference schemes it employs. This conceptual shift, thus, leads to the development of special-purpose computer programs, systems that are expert in some narrow problem area. These programs are called expert systems. How to extract, construct, and manipulate the domain knowledge constitutes the major concern in developing an expert system. A new set of principles, techniques, and development tools has emerged and that forms the basis for knowledge engineering [Feilcke, 1981; Reilly, 1984].

In comparison with algorithm-based computer programs of the conventional approach, the knowledge-based expert system is best distinguished by the characteristics of the problem domain it is applied to. It is not suitable to apply the algorithm-based conventional programming approach to expert system's problem domains. In these problem domains, tractable algorithmic solutions usually do not exist, since many important tasks are related to the intensive heuristic knowledge of a human expert, thus requiring precise description and rigorous analysis

Planning, legal reasoning, medical diagnosis, geological exploration, and analysis of military situations exemplify these problems. Contemporary methods of symbolic and mathematical reasoning, which have limited applicability to the area of expert systems, do not provide a means for representing knowledge, describing problems at multiple levels of abstraction, allocating problem-solving resources, controlling cooperative processes, and integrating diverse sources of knowledge in diagnosis. These functions depend primarily on a capacity to manipulate problem descriptions and to selectively apply relevant pieces of knowledge. The expert systems, depending on the application problem domain, are categorized into several types such as interpretation, prediction, diagnosis, design, planning, monitoring, debugging, repair, instruction, and control systems [Smith, 1983, 1984].

Expert systems are also distinguished by distinctive program structures from the algorithm-based programs of conventional approach. Expert systems typically consist of four major structural components, i.e., a knowledge base, a data base, a control mechanism, and a knowledge-base editor. In the expert system structure, emphasis is on the separation of domain knowledge from a separate knowledge base in the form of modularized pieces of independent knowledge. A control mechanism provides a general strategy in trying to match the relevant findings and data in the

data base to the knowledge base in order to derive a conclusion. Since, most of the domain knowledge is represented by a set of modularized pieces and is constructed in a separate knowledge base, the domain knowledge can be handled in a flexible and manageable way by a knowledge-base editor. The control mechanism can also be in a flexible and generalized form in the knowledge-based expert system structure. The knowledge-base editor, which is a user interface for the manipulation of the overall system, is also a distinguishing feature of an expert system, providing a flexible and managed environment for the user. Without any modification of program, a user can access and change the system knowledge through the knowledge-base editor. The expert system often possesses the capability to explain the line of reasoning for a conclusion through the knowledge-base editor.

Expert system architectures vary widely depending on their applications. The current techniques and principles of expert systems are based mostly on the relatively small number of early expert systems. Rule-based knowledge representation constitutes the major framework of the current expert system technologies [Belle]. Although the rule-based knowledge system is appealing because of its general expressive power and well-defined syntactic, more sophisticated reasoning schemes and architectures are required for many intrinsically harder problem domains,

These domains usually include the problems of a large search space of possible solutions, diversity of knowledge, dimensionality of data or knowledge (e.g. time, space), lack of fixed inference process to solve the problem effectively, handling of interactions among decisions of separate subproblems of the task, need for specialized representations, and incompleteness of data. A frame-based representation [Pilk] and a blackboard model approach [Deffo] are among the several advanced techniques to cope with these difficulties. A frame provides a structured representation of an object or a class of objects. Each class of objects can be described as a specialization (subclass) of other more generic classes, thus the classes are represented into hierarchies in organizing frames. The frame provides a concrete representation of useful relations, and supports a concrete definition-by-specialization technique that is easy for most domain experts to use. In addition, this representation structure provides automatic inferences as part of each assertion and retrieval operation. The taxonomic relationships among frames enable descriptive information to be shared among multiple frames via inheritance. The internal structure of frames enables an systematic maintenance of semantic integrity constraints. Production rules by themselves are inadequate to define names and to describe domain objects and static relationships among objects. Hybrid representations are

constructed by integrating frame and production rule representations, resulting in the consolidation of advantages of both representation techniques. The frames provide a rich structural representation for describing the objects referred to in the rules. The frames support a layer of generic deductive capability about those objects that do not need to be explicitly dealt with in the rules. Frame taxonomy can also be used to partition, index, and organize a system's production rules.

The blackboard model of problem solving is a highly structured special case of opportunistic problem solving [Re78]. In addition to opportunistic reasoning as a knowledge-application strategy, the blackboard model prescribes the organization of the domain knowledge, all agents, and intermediaries and partial solutions needed to solve the problem. The solution space is organized into one or more application-dependent hierarchies. The domain knowledge is partitioned into independent modules of knowledge that transform information on one level of the hierarchy into information on the same or other levels. The knowledge modules perform the transformation using algorithmic procedures or heuristic rules that generate verified or hypothetical transformations. Reasoning is applied within this overall organization of the solution space and task-specific knowledge. In other words, the module of knowledge to apply is determined dynamically, one

step at a time, resulting in the incremental generation of partial solutions. At each step of the knowledge application, either forward- or backward-reasoning methods can be applied.

### Application Examples And Future Prospects

#### Application Examples

One of the applications of expert system technology is in the building of medical consulting systems designed to aid in medical decision making (Levy, Rupp, 1984). Mycin (1974), Casnet (1976b), and Internist (1975, 1977) are among the examples of early expert systems which often referred to as typical expert system applications. The Mycin system was developed to provide consultative advice on diagnosis and therapy for infectious diseases. The system is in a form of a production rule based system and the uncertainty and incompleteness of data and knowledge are handled by the Certainty Factor scheme. Casnet is a computer system for medical diagnosis in the treatment of glaucoma. The system represents a disease not as a static state but as a dynamic process modeled by a network of causally linked pathophysiological states. The system diagnoses a patient by determining the pattern of pathophysiological causal pathways present in the patient and identifying this pattern with a disease category. Internist is a reasoning program

in the domain of internal medicine. Using the information preserved during the consultation, the program tries to discriminate between competing disease hypotheses. Thus, this system is of the type that verifies a hypothesis formation using the system's knowledge represented in the form of a disease tree, or disease taxonomy.

The application of expert systems in medicine was motivated by two major reasons. First, the expert computer-based system can provide great benefits by providing thorough and reliable diagnostic services. Considering that most of the errors made by the clinicians are caused by omissions involved in the diagnostic process, the computer can provide reliable diagnostics by an exhaustive consideration of all the possibilities and all the relevant patient's data. The second motivation is related to current research interests in application oriented artificial intelligence. Clinical medicine has been a fertile area for the study of cognitive processes, and diagnosis as a cognitive process has been studied extensively.

Historically, statistical analysis and pattern recognition, through a discriminant function based on the Bayesian decision theory, have been used for the development of computer analysis of medical diagnostic problems. The appeal of the statistical method is that the decisions based on such methods are optimal for given criteria. However,

the statistical approach is unavoidable in medical problems, because of various assumptions and simplifications such as independence and mutual exclusiveness of various disease states. These assumptions cannot be exactly validated and the a priori and conditional probabilities required in the analysis are usually not available.

The medical decision aid is a typical example of a heuristic domain which includes a large amount of domain specific medical knowledge and physicians' heuristic knowledge obtained through years of practice and experience with many special cases. The physicians provide a diagnosis based on the heuristic knowledge for handling incomplete data and uncertain information.

One of the difficulties in designing a medical consulting expert system with a human expert-like performance is that the human expertise comes from his capability to consider and handle a large number of special cases. As the spectrum of a task becomes larger, more and more of special considerations are involved in solving the problem. Moreover, the heuristic knowledge of a physician also involves a kind of commonsense knowledge obtained through a long period of experience and education, and this commonsense knowledge is immense in its nature and is usually very difficult to articulate and represent in a compactable form in a computer.

The development of computer-based consultation systems also brings many formidable social, physical, and ethical problems that must be considered in expert systems' design. These problems include validating the systems, exporting them to hospitals or laboratories, getting physicians and patients to accept them, and determining the level of responsibility for the clinical decisions made with the help of these systems. It is reported that the biases of medical personnel against computers are so strong that systems will eventually be rejected, regardless of performance [1972]. Thus, there exists another barrier in achieving a significant contribution of computer diagnosis consulting systems for routine applications.

Several expert system applications have been shown also in the domain of chemistry and other engineering and scientific application areas. General, Prospector, and Xcon systems are among the well-known expert system examples in those application areas.

General [Full, Fulls] generates plausible structural representations of organic molecules with data obtained from mass-spectrographic analysis of unknown molecules and with a set of rules used by an expert chemist to infer conclusions on molecular structures from such data. The elucidation of molecular structures is fundamental to the application of chemical knowledge to important problems in biology and medicine. In many circumstances, the powerful analytical

techniques of X-ray crystallography and X-ray fine structure analysis may not be applicable; consequently the analysis process is much too laborious and dependent on the intuitive expertise of chemists. Thus, there exists a legitimate reason for developing a computer aided expert system, and room for a significant contribution of the computer analysis.

In this type of molecular structure elucidation or chemical compound synthesis domain, the major problem aspect is a heuristic search in limiting the combinatorial explosion of all the possible structural candidates. However, the process of making up a set of rules about mass-spectrometry proves to be much too involved, since the theory of mass spectrometry is incomplete and the rules about it are laxest and difficult for experts to explicate.

The formal system's level of performance is generally far less than that of a human expert. This indicates the difficulty involved in codifying the human expert's skilled process in the system. However, there exists a possible contribution of computer analysis in the structure elucidation domain, because a computer can provide a systematic search through the space of possible molecular structures, a systematic use of what it does know to constrain the possible structures, and the calculating power to handle fair amount of calculations involved in the process.

Prospector is a computer-based consultation system for mineral exploration [Bart, 1979, 1980a]. The main function of Prospector is to match data from surface geological observations against models of five different types of deposits. In the Prospector system, contextual information and data are treated in the same plane of a probability propagation model, and the control scheme is heavily dependent upon the numerical comparisons. Thus, the system lacks flexibility for considering high level context information and situational considerations in an appropriate way. The model, which is based on the probability propagation, cannot provide a sufficient validation.

HEARSAY speech understanding system [Artis, 1978b] was developed in the domain of voice chat. This system was constructed with the idea of independent knowledge sources cooperatively solving a problem by passing hypotheses on a global blackboard data structure. Isolating the knowledge sources along functional lines provides efficient modification of the problem-solving structure of the program, by allowing a free substitution of independent subgoal knowledge sources. This modular structure, where the knowledge sources do not address each other directly, allows great flexibility as the system evolves and different combinations of knowledge sources and control strategies are tried. This blackboard structure has also been incorporated into several other systems solving diverse

tasks in crystallography, signal interpretation, vision, and psychological modeling.

### Limitations and Future Prospects

Expert knowledge consists of two abstractively described parts. First, it consists of the explicit descriptions that characterize the definitional, taxonomical, and empirical relationships in a domain and secondly, the procedures for manipulating these descriptions. To achieve a high-level of performance, a human expert's skills also need to be well understood and included in the system's knowledge base. A skilled process is usually related to fast response, efficiency, reduced error, reduced cognitive load, and increased adaptability and robustness. The term skill conveys the idea of appropriate knowledge and its effective use.

Most of the current expert systems are based on a limited number of knowledge-representation and inferencing techniques. However, there exist several fundamental limitations in realizing human-like intelligence in a computer by the present A.I. approaches which are mostly based on the description of features and rule-like inferences. The associated problems related to the massive commonsense knowledge and to the lack of knowledge for human being's recognition processes, such as image-based inference, similarity recognition, and relevance pruning

processes are avoided barriers to overcome the limitations of the current application-oriented A.I. technology in achieving a machine intelligence competitive with a human expert's level of performance.

Based on this assertion, A.I. and in particular the expert system approaches are severely criticized in the book by H.-G. Greiffes and H.-G. Greiffes [Gr85]. It states that it is impossible to achieve a computer system which can show human expert level performance incorporating human expert-like processes. This opinion is appealing considering that the fundamental questions raised regarding the human cognitive processes are not answered and most of the current techniques are based on superficial simulations. More importantly, expert level performance is related to the human expert's capability for considering large numbers of special cases involving commonsense knowledge obtained through many years of experience and education. If the crucial key to obtaining the human expert-like performance is in the modification of this huge amount of heuristic knowledge, there exists a fundamental barrier to this approach. The heuristic knowledge is inherently difficult to codify into the system, and the amount of knowledge easily exceeds the manageable range of a computer. They also point out that most of the optimistic reports regarding the early expert system examples are misleading, in the sense that, the status of the systems are in reality far

from routine applications. A system's high performance, if any, is not due to machine intelligence and A.I., but to the computer's other superior aspects over human beings in handling data-intensive or calculation-intensive portions of the total task. This is exemplified in the Internist and the General systems. It is also noticeable that no other systems ever attracted more attention than those early application examples mentioned above, implying a difficulty in expert system approach for routine applications.

However, there is unfortunately very little that can be offered as a constructive counter-proposal, for solving heuristic problems by a computer with a human-like level of performance and intelligence, that is not somewhat vague and hand-waving. It is more reasonable to accept the A.I. and expert system approach as a new way to solve different aspects of a problem in which conventional approaches cannot offer a suitable solution. Selection of an appropriate domain, then, will be a significant issue in successful applications of the expert system approach. Considering the present status of A.I. and expert system technology, it is more reasonable to select a domain such that the expert system approach can give a complementary contribution to solving the heuristic portion of the whole task. The whole task still involves applications of conventional engineering or computer technologies and/or requires computer's superior calculating power to handle a fair amount of data-intensive

and calculation-intensive portions of the tasks. The problem domain also needs to be selected by taking into consideration the amount of knowledge to be incorporated into the system such that it does not exceed the manageable range of the computer. It is also better to avoid the problems if a validation from the domain professionals is a significant barrier, thus it is difficult to be accepted by the domain professionals because of the social, ethical, cultural, and other complicated problems, as shown in the medical diagnostic expert systems.

CHAPTER IV  
KNOWLEDGE-BASED SIGNAL PROCESSING SYSTEM

Sleep EEG Analyzing Domain And  
The Design Considerations

Sleep EEG Analyzing Domain

Human sleep EEG/EOG/EMG data are analyzed by a human scorer through the visual perception and interpretation of the multi-channel data on a polygraph chart. This process is best interpreted as primarily a pattern matching and classification based on heuristically obtained knowledge in the form of templates for the waveforms and sleep stages. The sleep data analysis, thus, falls into an application domain category of data interpretation by classification.

The expert classifies a segment of the record into one of the five sleep stages plus awake by interpreting the data according to the perceived information, within the epoch, and other contextual information. In the process of visual scoring, the human expert perceives the occurrences of waveform activities, such as alpha, beta, delta, edges, theta, muscle artifacts, rapid eye movement, etc., by a global observation of the multi-channel sleep EEG/EOG/EMG data on a polygraph chart.

Most of the patterns and templates do not readily exist in a fixed and definable form, since each segment of

the Record must be interpreted in a different context according to the individual subject's signal characteristics, several adjacent epoch patterns, and other higher order contextual situations which may affect the sleep stage scoring. Templates have to be articulated and extracted from the equivalent ones that are in the form of the expert's heuristic knowledge which comprises all the contextual data interpretations. The expert's knowledge is obtained by an intensive training process and is qualitatively applied to the visual inspection of the record.

In 1968, Rechtschaffen and Kales created a set of sleep stage scoring criteria that provide a standard reference for sleep stage scoring among researchers [Kales]. A brief summary of these criteria is listed below.

**Stage Wake (Stage 0):** This stage corresponds to the waking state. It is characterized by alpha activity and/or a low voltage, mixed frequency EEG. Certain subjects may have a virtually continuous alpha activity; other subjects may show little or no alpha activity in the record. This stage is usually accompanied by a relatively high tonic EMG, and often REMs and eye blinks are present in the EEG tracing.

**Stage 1:** This stage is defined by a relatively low voltage, mixed frequency EEG with a noticeable theta activity. Stage 1 occurs most often in the transition from wakefulness to the other sleep stages or following body

movements during sleep in normal subjects. During nocturnal sleep, Stage 1 tends to be relatively short, ranging from 1 to 7 min. Scoring of Stage 1 requires an absence of clearly defined K-complexes and alpha spindles. Stage 2, especially following wakefulness, is characterized by the presence of slow eye movements, each of several seconds duration, which are usually most prominent during the early portions of the stage. Rapid eye movements are absent. Tonia and bursts are usually below those of relaxed wakefulness. The transition from a high-alpha subject wake state to Stage 1 is characterized by a decrease in the amount of alpha activity. Fifty percent (50 %) of the epoch is used as the boundary for separation of Stage 0 and Stage 1.

Stage 2: This stage is defined by the presence of alpha spindles and/or K-complexes and an absence of sufficient delta activity to define the presence of Stage 3 and 4. If less than 3 minutes of the record which would ordinarily meet the requirements for Stage 1 intervene between two epochs of Stage 2, those intervening epochs are to be scored Stage 2. If there is no indication of movement arousal or pronounced increase in wake time during the interval in question.

Stage 3: Stage 3 is defined by an EEG record in which at least 25 % but not more than 50 % of the epoch consists of delta activity.

Stage 4) Stage 4 is defined by an EEG record in which more than 50 % of the epoch consists of delta activity. Intervals between delta waves rarely persist for more than a few seconds in Stage 4, but are usually prominent in Stage 3 epochs. Alpha spindles may or may not be present in Stage 4.

Stage REM. Stage REM is defined by the concomitant appearance of relatively low voltage, slow frequency EEG activity and episodic REMs. The EEG pattern resembles the one described for Stage 1, except the vertex sharp waves are not prominent in Stage REM. Alpha activity is usually somewhat more prominent in Stage REM than in Stage 1. As with the EEG of Stage 1, there is an absolute absence of alpha spindles and K-complexes. Stage REM should not be scored in the presence of a relatively elevated methyl-substituted EEG.

These criteria define the patterns of each sleep stage in terms of the number of occurrences of specific waveforms, total time of specific waveform activity in an epoch, and/or the amplitude level description of the record (Ag72, Rechtschaffen). For some waveforms such as alpha spindle, K-complex, and REM, the number of occurrences is used in the criteria. For the other waveforms the total duration time of waveform activity within an epoch determines the criteria. The Rechtschaffen and Kales criteria, however, are a minimum set of quantitative specifications which can be used only as

a general guide for sleep stage scoring and training of human scorers. The actual sleep stage scoring is performed by incorporating such more heuristic knowledge for the contextual interpretation. The actual EEG data processing is based on a gestalt perception of waveform activities together with a heuristic interpretation of the record and is not based on a precise and analytic measurement of the data.

### Design Considerations

Several design considerations for developing an expert system for the automated sleep EEG/ECG/EMG signal analysis are discussed in the following. For sleep stage scoring, the on-line data processing aspect of an automated system is a distinguishing factor from other contemporary expert systems. Other related special design considerations like reasoning and processing efficiency, architectural effectiveness, reasoning with uncertainty, and adaptiveness of the system are discussed.

To date, expert system design is limited to a few knowledge representations and inferencing methodologies which are exemplified through the earlier applications in the medical domain, chemical structure construction domain, and other engineering or scientific application domains [Belle, Burdo, Cohn], which are reviewed in Chapter III. If-then production rules provide a very efficient way of

representing knowledge in the application domains where judgemental knowledge constitutes a major portion of the expert domain knowledge [Ruff, Ruff]. Semantic network and frame based knowledge representation [FIS] provide a more structured way of representing knowledge when the domain knowledge includes sophisticated interrelationships or hierarchical dependencies among diverse subjects of the knowledge. Most of the current inferencing methodologies are based on a data-driven forward chaining scheme, a goal-driven backward chaining scheme, or other opportunistic methods [Ruff, Ruff] which combine the two basic schemes resulting in improved search efficiency. Several expert system development tools have been also developed to provide a generalized way of expert system development by incorporating these basic knowledge representations and inferencing methodologies. Examples of these tools are EMYCIN, ROSE, EXP, ALL, AGO, etc., [Ruff]. However, most of these readily available tools bring restrictive limitations in system design; thus, applications of these tools are generally confined only to certain limited application domains. In general, the development of an expert system can not totally depend on any of the previously developed design methodologies; it needs to be carefully designed by considering all the problem specific features and constraints by employing new representation schemes or inferencing methodologies.

In designing an expert system, several complications may arise. The diversity of domain knowledge is one of the most typical problems which greatly affect the design and applicability of the system. A domain's knowledge is heterogeneous when it consists of several different subtasks combined in complex relations and/or when it employs several layers in terms of depth and fineness of knowledge. The Internist system demonstrates a good example of the knowledge diversity which results from the various subtasks in the domain's knowledge [PoFF]. The Crysalis system also exemplifies knowledge diversity related to the wide range of depth and fineness of the domain's knowledge [HeFF]. The knowledge diversity is, in most cases, handled by the idea of partitioning of knowledge sources, hierarchical construction of the domain knowledge, or a combined scheme of these. The partitioning of the domain knowledge is exemplified in the following systems: Internist, Deduct [LISB], Casnet [McFib], and Prospector [DeFF]. The systems Crysalis, Kearney [McFib], and Casnet are cases of handling the knowledge diversity problem using hierarchical construction of the domain knowledge. Recently, these concepts have been more generalized and referred to as the blackboard structure [McFF, McFib, Nidd] where all levels of knowledge sources and their temporary results are stored and are used as a global data structure for inducing a particular hypothesis.

The sleep EEG analyzing domain shows the problem of knowledge diversity which is associated with the existence of different processing layers when the human scorer's analyzing process is modeled in an expert system. Each processing layer is associated with a different processing time-frame and with a different type of processing knowledge. This layered hierarchy of the domain knowledge calls for designing the system in a layered blackboard model architecture.

The sleep EEG analyzing process is broken down into three different layers of hierarchy: recognition of waveform activities at the bottom level; template matching at the next level where each record segment is classified according to the pertained information in the speech, and contextual interpretation at the highest level of processing. This layered hierarchy provides the basic framework for handling the diverse knowledge sources, increasing the processing efficiency for on-line data processing.

The human scorer's visual scoring process is simulated as a single-pass processing for the speech-like classification of the entire night's data in a strict bottom-up fashion on the blackboard model hierarchy. In the design of a sleep EEG analyzing expert system, the single-pass processing capability is emphasized for the on-line processing aspect of the system. However, the human scorer's visual scoring process involves a multi-pass

inspection of data within a certain length of record to analyze an epoch in the context of several adjacent epochs. The human expert's localized multi-pass inspection is reflected in the design by using higher level abstracted data in a sliding window of five consecutive epochs.

This single-pass processing model features a noticeable difference between the sleep EEG domain and most other application domains, where a multi-pass problem solving structure is generally important. In these domains, initial or partial solutions are continuously refined further by interactive new inputs from the user and/or by other relevant findings from one of the knowledge sources until a set of solutions for the problem is obtained.

The system recognizes and counts the time or number of waveform activities in each 30 second epoch. The waveforms are recognized at the early-processing system as described in chapter II. The number of waveforms is counted for alpha spindles, X-complexes, and rapid eye movements. The total running time of waveform activity is obtained for alpha spindles, beta spindles, delta, theta spindles, muscle artifact, and slow eye movements. The ESD is described by an amplitude level as high, medium, or low. In obtaining the total running time of these waveform activities within an epoch, an appropriate smoothing should be applied to get a closer agreement with the human expert, since smoothing is implicitly employed in the process of the waveform activity

time detection by the human scorer. In the system, if a waveform activity contains an interval of less than one second without the waveform activity, the interval is considered part of the waveform activity running time. The early-processing always involves the possibility of an error due to the wide variabilities of signal characteristics. Since the detection reliability depends upon the detector and is different among the detectors, each waveform detector output is associated with one of the three reliability factors, i.e., High, Medium, and Low. Presently, the alpha and mu-mu artifact are assigned a high reliability factor, the beta, delta, edges, EEM, and EEN are assigned the medium level reliability factor, and theta activity and X-complexes are assigned a low level reliability factor. These reliability factors can be assigned differently through the system's knowledge-base editor.

Each record segment (usually 30 or 60 seconds) is classified into one of six stages based on the perceived information in the speech using the template matching rules. These rules comprise the Rechtschaffen and Kales sleep stage scoring criteria. The efficiency of an inferencing scheme is closely related to the number of possible solutions. If the size of this solution space is too large, it is almost impossible to find a solution by trying all the possible hypotheses. Examples of this have been shown in classical molecular elucidation or syntactic problems, and other such

designs and configuration applications. In this case, the data-driven plan-generator-test scheme [Holl8a, Holl8b] is used as a search and proving scheme to locate the possible answer efficiently as shown in General and Crystal systems. On the other hand, in the medical domain, an omission of possible hypothesis may create a critical error in terms of diagnosis. Thus, an exhaustive search by attempting all the possible hypotheses is appealing. The Hxsis system does the exhaustive search based on the goal-driven backward chaining inferencing. The sleep IED domain also has a finite set of goal hypotheses and an exhaustive search scheme can be efficiently applied based on the backward chaining inferencing. However, an efficient time-performance of the system is crucial in the design of an on-line processing system. Thus, a dynamic scheduling of searching sequences is devised as a scheme to improve reasoning efficiency using the high level contextual information of the sliding window in the blackboard hierarchy. The dynamic rescheduling of search sequences is most effective in improving reasoning efficiency when it is applied to a higher level knowledge. The overhead when a rescheduling is applied to a lower level knowledge, on the other hand, reduces the efficiency of the overall system, because the search space size is generally much larger for the lower level knowledge.

At the top level, the human doctor's scanning process is modeled with a sliding window included in the system.

The beam scorer scans the scanned speech-by-speech for an epoch-wise classification. In the epoch-wise classification, the scorer often refers to the information of preceding and succeeding epochs to classify an epoch in a context of the multiple epochs. The sliding window includes the global features of several adjacent epochs, for the high level context interpretation. Five consecutive epochs' stage classifications and associated certainty levels constitute the high level abstracted information of the sliding window. These data reflect most of the context information that gives significant influence to the classification of each epoch. Each epoch's stage classification, which is first derived at the intermediate level by the template matching and classification knowledge, can be re-examined in a broader context provided by the sliding window. The window slides epoch-by-epoch representing a scanning procedure similar to that of the beam scorer. This sliding window constitutes the highest level information piece of the blackboard and provides a distinctive structural feature resulting with an improvement in processing efficiency.

Incompleteness and uncertainty of data, and the lack of information and knowledge are inherent problems in any application domains. Appropriate representation and interpretation of these uncertainties are intrinsically difficult problems [Ogaki]. Most of the methods developed to

date rely on some intuition and empirical treatment of numerical values using either a probabilistic or a non-probabilistic approach [Luft, Adhi, Luft]. These models are designed with an emphasis on end-results in achieving a certain level of performance. A systematic management of the uncertainty problem is also emphasized in designing the models. On the other hand, they lack a theoretical basis and contain certain shortcomings, creating limitations in the application of the models as a general approach.

The Bayesian conditional probability theory provides a reasonable groundwork for the treatment of uncertainty, but the assumption of the rationalness and the requirement of thorough a priori knowledge make it non-feasible for many applications.

In Mycin system, the Certainty Factor (CF) model is developed based on the conceptual framework of combination and dissociation to represent the level of an expert's belief within a piece of knowledge [SMPS]. Empirical combination functions are devised to obtain a certainty level from more than one evidence. A certain level of threshold (0.3) is used when judging the success of a rule execution in the inferring step. The Mycin's CF model provides a good systematic approach to overcome several shortcomings of Bayesian conditional probability theory. The Mycin's CF approach does not require the statistical data, but relies on the approximated raw variables which

convey an idea of confidence and disconfirmation of the expert. This technique is not exact, but since the conditional probabilities reflect judgemental knowledge, which is highly subjective, a rigorous application of Bayes' theorem will not necessarily produce accurate conditional probabilities either. However, the definitions of the CF and its manipulation scheme can not provide a concrete theoretical basis, since the technique and its validation are totally based on empirical judgement. The application of the CF model involves several limitations of its own. The suitability of the CF scheme is thus very dependent on the nature of the problem domain.

Limitations of the Mycin-like CF model have been well exemplified in the previous research [1986] of our laboratory work, the Dempster-Shafer theory, which provides a generalized model for the Mycin certainty factor scheme, was applied to the sleep EEG scoring problem. The sleep EEG scoring problem was modeled as a finite automata machine and the Dempster-Shafer model provided a numeric measure for the transition mechanism. It was ascertained that the numeric values (certainty factors) and their operations do not provide a sufficient measure of the transition mechanism for a correct sleep stage derivation. In the sleep EEG scoring problem, information from several adjacent epochs significantly influences the classification of an epoch's stage. Thus, the classification of an epoch cannot totally

depend on the transition scheme which is based on the comparison of numeric values. The values reflect the levels of an agent's existing predefined sleep stages template. It is necessary to provide a different representation and combining scheme of the certainty factor to provide an appropriate measure for the contextual interpretation.

In this research, a new model is designed for the management of uncertainty and incompleteness. The model is designed with a pragmatic reason to overcome several shortcomings of the prior certainty factor models and Bayesian conditional probability theory models which appear when these models are directly applied to the EEG analysis domain.

The new uncertainty handling model uses linguistic variables, i.e., High (H), Medium (M), and Low (L), instead of numeric values. The human expert describes his confidence in data and knowledge by associating it with one of the discrete certainty variables. In this way, the TRUE part of each rule is associated with one or more of the certainty variables according to the number of action elements in the THEN part. As an example, Alpha is described as High-Activity when the sum of alpha waveforms exceeding time exceeds 15 seconds within the epoch. However, the certainty level is determined according to the following transmission scheme: the certainty variable is H if the activity time exceeds 15 seconds, M if the activity

time is between 20 and 25 seconds, and L is the activity time is between 25 and 30 seconds. These linguistic variables reasonably reflect the human expert's belief level in a natural way and provide a conceivable method of handling uncertainties.

A new combination scheme is defined with the discrete certainty variables based on the conceptual framework of extending the weight with the certainty levels. The detailed description of the combination scheme and its operation are shown with an example in the next section on design and implementation. The newly defined combination scheme and the discrete certainty variables provide a kind of robustness in inferring steps, preventing propagation of minor variations of certainty levels. In this scheme, the certainty level of an assertion changes only when the combined level of certainties in evidence exceeds a certain level. This combining scheme and the linguistic variables also provide an appropriate way to represent the uncertainties in a form of conceivable template. Since the uncertainty is abstracted and represented as a part of the conceivable template, this uncertainty handling model provides an efficient way to implement the contextual manipulations in the conceptual framework of template matching.

The human expert's sleep EEG analysis is regarded as a process of template matching. The variations in the data

and the lack of information result in ambiguities when an epoch is matched against any of the templates. The ambiguous epoch is understood in terms of the context of several adjacent epochs by the solver. This solving process is robust over the minor variations of data in the record. This overall processing, when implemented in a computer, calls for an uncertainty handling model that must reflect the strengths of the template matchings for the classifications and contextual interpretations. The comparison of the numerical values of relative likelihood (RL) as implemented in the Hsiao system does not represent properly the uncertainty handling of sleep EEG processing, where template matchings and strong contextual re-examinations play a main role in the processing. The operation of the new uncertainty handling model does not rely on analytic number operations. The fact that, an expert's gestalt solving results in a better performance than a rigorous analysis done by a novice, illustrates that the superiority and efficiency of an expert comes from the robustness of the expert's knowledge for interpreting an acoustic epoch in a context, and from any capability for numerical operations.

## Design And Implementation

### Functional Description of the Overall System

The entire night's data of recognized waveforms is acquired on-line at the host computer and analyzed by the token processing system for sleep stage scoring. The token processing system is implemented in C++ on the IBM RS/6000 PC. The overall functional block diagram of the knowledge-based token processing system is shown in Fig. 4.1, and each functional block is briefly described in the following. Major structural components of the system are a data base, a knowledge base, a knowledge engine (control module), a knowledge-base editor, and other interfaces for an explanation mechanism as is shown in Fig. 4.1.

The data base consists of two parts, a static data base and a dynamic data base. The static data base contains the night's token data received from the early-processing system. The dynamic data base contains three layers of temporary data planes, in a blackboard model architecture, which are continuously updated during the system epoch-wise consideration of the record.

The knowledge base consists of three different layers of knowledge which are each associated with a corresponding data plane in the blackboard. The three layers are a parametric feature extraction knowledge at the bottom level, template matching and classification knowledge at the next

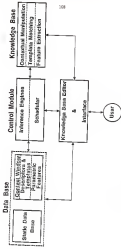


Fig. 1 Knowledge-Based Fault Processing System Control Functions Block Diagram

level, and contextual interpretation knowledge at the top level of the knowledge base. The knowledge is represented in if-then production rules effectively reflecting most of the domain knowledge.

The primary role of the knowledge engine, which is composed of rule-interpreters and a scheduler, is to derive an epoch's sleep stage using the rules contained in the knowledge base and corresponding data in the Measurement data planes. The scheduler performs a global control over the knowledge base and data planes. It also performs a scheduling of search sequences of the intermediate level inference engine according to the high level contextual information in a sliding window with an improvement in searching efficiency of the system. Explanations about the epoch classification can be explored at any depth and any range of related information in the system. Besides this on-line explanation facility, the system also provides an off-line explanation feature loaded with a series of rule identification codes, which can be used after the system has finished processing the night's data.

The expert system development includes the development of an expert system shell with a knowledge-base editor. The knowledge-base editor allows the creation and modification of the knowledge base without any modification of the program by the user. The knowledge-base editor, which is closely related to the knowledge representation

scheme and the system's inferencing mechanism, is designed considering the flexibility for future extension or modification of the system as is described in the next section. A menu-driven user-friendly interface is designed for the editor.

### Structure of Knowledge Base and Data Base

The system's knowledge base is structured in three layers of hierarchy consisting of three different levels of knowledge: the parasitic feature extracting knowledge, the template matching and classification knowledge, and the derived interpretation knowledge. Each level knowledge is referred to as a knowledge source (K.S.) in the layered knowledge base. The knowledge base, thus, consists of the three knowledge sources: parasitic level K.S., speech level K.S., and context level K.S. as illustrated in Fig. 4.1. The blackboard structure of the data base corresponds to the hierarchical organization of the knowledge base. The blackboard contains all the input data and intermediate solution states produced by the knowledge sources; it is hierarchically layered according to the level of analysis. The knowledge sources use this blackboard as a global data base to derive further solutions.

The domain knowledge is effectively represented by if-then production rules, since most of the domain knowledge is in the form of judgemental knowledge. Each level

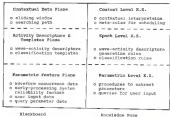


Fig. 4.3. The Blackboard Model Hierarchy of The System

knowledge is associated with a corresponding rule-interpreter (inference engine). The scheduler globally arranges the rule-interpreters.

The layered structures of the knowledge base and blackboard are illustrated in Fig. 4.2. The parametric level knowledge includes procedures which extract parametric data from the user and from the multidatabase record. The set of parameter values which constitutes the bottom level parametric data plane includes waveform occurrence values within an epoch, waveform detection reliability factors of the early-processing system, query parameter values, and user input data like sex, age, record number, and date. These parameter values constitute the bottom level of the blackboard. Sample parameters from the parametric feature plane are illustrated in Fig. 4.3. For all the waveform occurrence parameters, such as signal-time, data-time, signal-count, etc., the waveform activity time or number of occurrence in an epoch is assigned together with the waveform detection reliability factor. The early-processing detection reliability factors are stored in the system knowledge base and can be modified through the knowledge-base editor. The query parameters, such as Subject-signal, Under-drug, and , are variables which reflect a priori knowledge of subject dependent characteristics. These parameters can be incorporated in the system's scoring rules according to the purpose. Any number of query parameters,

Alpha-t12a	Beta-t12a
Beta-t12a	Theta-t12a
Delta-count	Gamma-t12a
EEG-t12a	REM-count
Rem-count	Subject-Alpha
Subject-Beta	Under-draw
Alpha-reliability	Inter-rater-reliability
Beta-reliability	Alpha-reliability
Theta-reliability	Beta-reliability
REM-reliability	REM-reliability

Fig. 4.3. Sample Parameters of the Parametric Feature Plane.

WAKE-W-ACTIVITY	SLEEP-W-ACTIVITY
ALPHA-ACTIVITY	BETA-ACTIVITY
DELTA-ACTIVITY	SLUGS-ACTIVITY
THETA-ACTIVITY	MUSCLE-ACTIVITY
REM-ACTIVITY	REM-ACTIVITY
SCOR-ACTIVITY	

Fig. 4.4. An Sample List of Wave-activity Descriptors.

which can also be modified through the knowledge-base editor, can be defined in advance in the knowledge base with a default value and an associated certainty level. Before the system starts speech-by-speech classification of the entire night's data, the system displays the default value of each query parameter, and asks the user if he wants to change the value. In this way, all the a priori knowledge of the subject can be incorporated into the system. Since, these values are input to the system only at the beginning of processing, the system can run without any further user's intervention.

The intermediate level knowledge represents the human expert's problem of template matching for the classification of each record segment. Templates are mostly articulated and extracted from the human expert's heuristic knowledge and are defined in the form of a production rule. Combined information of several wave-activity descriptions represents a template. This level knowledge also includes the rules which derive the wave-activity descriptions of an epoch using the waveform occurrence data in the parameteric feature plane of the bottom layer. A sample list of wave-activity descriptions and template matching rules are illustrated in Fig. 4.4 and 4.5, respectively.

A rule consists of a rule identification code, a premise, an action, an either, a date, and a justification. The rules are stored internally in a link code and consist

## RULE-1: 0-14

Premise: [(H) ALPHA-ACTIVITY MED] (H) MUSCLE-ACTIVITY MED)

Action: (WAKE-W-ACTIVITY HIGH L)

Author: (TAD GY (HAGG))

Date: (8-5-1988)

Justification: If an epoch is described as both medium ALPHA-ACTIVITY and medium MUSCLE-ACTIVITY, then the epoch is described as high WAKE-W-ACTIVITY.

## RULE-1: 0-14

Premise: [(NOT WAKE-W-ACTIVITY HIGH) (NOT REM LOW) (H) SLEEP-W-ACTIVITY LOW] (NOT WAKE-W-ACTIVITY HIGH) (H) DELTA-ACTIVITY LOW)

Action: (STAGE STAGES HIGH)

Author: (TAD GY (HAGG))

Date: (8-5-1988)

Justification: If an epoch after 50 minutes from the beginning of the record shows REM, low SLEEP-W-ACTIVITY, low DELTA-ACTIVITY, and not high WAKE-W-ACTIVITY, then the epoch is added as (STAGE).

Fig. 4 B. Examples of Rules for Classification.

of the following properties:

- 1) **SENT-ID**: An id is a form of a node.
- 2) **PREDICE**: A list is a form of (operator parameter value) or is a form of node that use of the three-tuple as (operator parameter value) ( . . -) [ ]. The predicator of PR, IT, EQ, and NOT constitute the operator set.
- 3) **ATTACH**: A list is the form of (parameter value certainty-factor) or a list containing more than one of this basic three-tuple form.
- 4) **AUTHOR**: A list containing the name of the author.
- 5) **DATE**: A list in a form of (month date year)
- 6) **JUSTIFICATION**: A list containing an English version of the translation to be used in the explanation mechanism.

The top level knowledge source includes contextual manipulation rules for the re-examination of an speech's stage classification and search sequence scheduling rules. These rules use the contextual information in the sliding window.

The sliding window contains the information of five consecutive speech to reflect a local context information in the search. This information contains speech stage stages, derived with the intermediate level template matching knowledge sources, and associated certainty levels of the

epoch stages.

The contextual manipulation is performed by the process of watching the sliding window with a set of templates in the form of If-then production rules contained in the context level knowledge source. The contextual interpretation rules continuously update the sliding window, possibly more than once each time the window moves one epoch. The process of watching is tried sequentially with the set of templates from the first one to the last one. Whenever a template matches with the sliding window, the window is updated by the rule and the process of watching starts again from the first template. This process stops when there are no more rules which match with the window. The sliding window will then slide one epoch position and receive a new epoch's classification stage and a certainty level from the intermediate level processing, for the next cycle of watching process. If the template side of a contextual manipulation rule is less than five epochs, the template slides through the window from left to right (equivalently from the oldest epoch to the most recent epoch) continuously updating the sliding window whenever a watching occurs. This process stops again if no watching occurs in the past cycle and stops if no watching occurs in the past cycle. This higher level contextual interpretation capability is especially crucial for a domain like sleep EEG analysis where human experts also perform a lot of

re-arrangement is a context of several adjacent speech's information. The inherent nature of wide variability associated with the sleep EEG characteristics adds to the requirement of the contextual manipulation of the data.

The information in a sliding window also provides for a heuristic search by reestablishing the searching path of the top-level goal hypothesis, i.e., stages 0 to 5, for the intermediate level template matching and classification knowledge. According to the context information collected in a sliding window, a searching path for the next speech is reestablished in the order of the likelihood of each top-level hypothesis. As an example, if the previous record segments show a running streak of stage two, the most likely stage for the next speech is also stage two and the next five stages are further arranged in the order of their likelihood, e.g., stage three, one, five, zero, and four. The scheduling is also performed by the template matching of the sliding window against the scheduling rules in the context level knowledge source. The scheduling is performed at the end of every speech's processing. The matching is tried sequentially on the set of scheduling rules. When a scheduling rule matches with the window, the new search path information is stored into the contextual data plane. This reestablishing provides a searching efficiency reducing the processing time without any significant overhead at the scheduling process. This searching mechanism feature is

Distinctively different from the exhaustive searching method used in the Mycin-like medicine consulting program. In Fig 4-4, an example of a sliding window is illustrated together with a contextual smoothing rule and a scheduling rule.

The top level knowledge base is described by four global variables. These variables allow an access to all of the contained knowledge. These variables are as follows.

- 1) **CONTEXT**: The value of this variable is a phrase which describes the knowledge base contained in the system. This phrase is displayed whenever the execution of the system is started.
- 2) **CONTEXT**: This variable is a list of atoms, here "list" and "atom" refer to the objects of Lisp programming language, which are the names of the contexts. The knowledge-base editor allows the user to input more than one context name. However, this feature is provided only for the flexibility of the knowledge-base editor. This system design is based on the hierarchy of the knowledge sources and the backward structure. Search spaces are grouped and searching efficiency is obtained by a dynamic rescheduling. Thus, one context is used in the system.
- 3) **PARAMETERS**: This is a list of atoms where each atom is a name of a group of associated

WINDOW	WINDOW-POS	a-1 a-2 a-3 a-4 a-5
	CERTAINTY-POS	1 1 1 1 1
Speech Stage-Frame		00
Scheduling Path		a-1 a-2 a-3 a-4 a-5

## RULE-2: 0-12

Premise: (EQ WINDOW [a-4 1 a-3 1 a-2 1 a-1 1 a-5 0])

Action: (WINDOW 0-a-4 1 a-4 1 a-3 1 a-2 1 a-1 1 a-5 0)

Action: (TAG CTS CHANGED)

Data: (1 7 1000)

Justification:--If three STAGE 3 speech which have an ambiguity, equivalently the lowest certainty level, intervene between two clear STAGE 4 speech, then the intervening speech was smoothed into STAGE 4 with the lowest certainty level.

## RULE-3: 0-1

Premise: (EQ WINDOW (\* \* \* \* \* a-4 \*))

Action: (FRAME [a-2 a-3 a-1 a-5 a-0 a-1] \*)

Action: (TAG STG CHANGED)

Data: (1 7 1000)

Justification: If the stage stage of the last speech in a running window is a-2, then the searching path for the next hypothesis is in the order of stage 1, 3, 1, 5, 0, and 4.

## Fig. 4.4

An Example of a Sliding Window (top), a contextual Manipulation Rule (middle), and a Scheduling Rule (bottom).

parameters. Also here, the knowledge-base editor allows the user to enter more than one parameter group.

- 4) **KNOWLEDGEBASE:** A list of rules where each rule is the name of a group of associated rules. The Knowledge-base editor accepts the definition of more than one rule group.

A context is described by the following named properties.

- 1) **FRAME:** A text containing an English phrase describing what problem the system is attempting to solve.
- 2) **DISPLAYFRAME:** A list containing an introductory phrase which is displayed directly below the value of **FRAME** whenever the system starts to execute.
- 3) **TEXTS:** This is an atom which has as its value the set of names of text lists which are associated with the context.
- 4) **PARAMS:** This is an atom which has as its value the set of names of parameters associated with the context.
- 5) **CREATEDATE:** A list containing the date on which the context is created. This list is of the form (A B C) where A represents the month, B represents the date and C represents the year.

This data is also used as a default data for the rule insertion or deletion.

- 6) **AUTHOR:** This is a list containing the full name of the creator of this context. This author name is also used as a default author name during rule insertion or editing.
- 7) **VALUES:** A list of parameters for which the system is trying to find values. In this system, one goal parameter exist, i.e., **STATE**.

A parameter consists of the following properties.

- 1) **TRANS:** A list containing an English phrase which is a translation for the parameter. This is used in the explanation mechanism.
- 2) **NO-TRANS:** A list containing an English phrase which is a translation for this parameter not being present. This property is associated only with YES/NO type parameters.
- 3) **PROMPT:** A list containing an English phrase which is used to ask for a value for this parameter.
- 4) **DERIVABLE:** An atom which is either T or NIL. It identifies whether this parameter has to be read from the data base at the bottom layer when it is needed (NIL) or whether the system should search first for a rule that can derive it (T).
- 5) **TYPEPARAM:** An atom which specifies the type of

the parameter value.

- a) **EXPECTED**: A list of expected values. This property is associated with parameters which have **TYPEDVAL** as **NOT** only. Not all the property values should be associated with each parameter. Examples of parameters are shown in Fig. 4.7.

A text is a list of words which is associated with **SQL** parameters. The text has a single property called **TEXT** which is a list of English words that is displayed if the corresponding rule fires.

### Inferring and Control Mechanism

Generally, in a blackboard modeling approach, each independent knowledge source is associated with a different reasoning and representation method according to its characteristics. Since most of the **SQL** domain knowledge can be effectively represented in a form of production rule, allowing a uniformity in the knowledge base structure, the if-then production rule based representation method is used.

The parametric database extraction knowledge at the bottom level includes the procedures which receive user query inputs and extract parameters from token data as is described before. The user query inputs are acquired into the system only at the beginning of the system run to allow a stand-alone running of the system without any

Parameter Name: WAKE-W-ACTIVITY

TRANS: The STAGE WAKE related EEG activities of the epoch, equivalently the combined level of activity of ALPHA and MUSCLE related,

WAKE-TRANS: All

PROMPT: What is the level of STAGE WAKE related EEG activities of the epoch?

DERIVEDfrom: T

TYPECODE: ANY

EXPECT: (HIGH MID LOW NONE)

Parameter Name: SLEEP-W-ACTIVITY

TRANS: The STAGE S related EEG activities of the epoch, equivalently the combined level of activity of SLOWA spindle and K-complexes.

SLEEP-TRANS: All

PROMPT: What is the level of STAGE S related EEG activities of the epoch?

DERIVEDfrom: T

TYPECODE: ANY

EXPECT: (HIGH MID LOW NONE)

Fig. 4-7. The Sample Property Lists for the Parameters of WAKE-W-ACTIVITY and SLEEP-W-ACTIVITY.

Intermediates.

The reasoning method for the intermediate level template matching is a goal-driven backward chaining scheme. The limited number of goal hypotheses, i.e., alias stages, make it very efficient to apply a goal-driven backward reasoning inferring scheme. It is implemented with the following procedures:

1. The system initially identifies the goal parameter *IFSM* as a goal for which it is attempting to find values.
2. The system first reads the hypothesis sequence from the hypothesis list.
3. The system then starts to verify those hypotheses sequentially, and it stops when one of the goal hypotheses is verified.
4. To verify a hypothesis, which also includes the goal hypothesis, the system first searches the fact list, which is the intermediate level data plane containing all the derived facts. A hypothesis is a list in a form of three-tuple, i.e., (operator parameter value), constituting a rule premise or a part of a rule premise. A fact in the fact list is a list in a form of three-tuple, i.e., (parameter value certainty-level). If the hypothesis does not exist in the fact list then the system checks to see if the

DERIVEDFIRST property of the parameter of the hypothesis is T or NIL. If it is NIL, the system reads the value from the bottom layer data plane and stores the value in the fact list. If the DERIVEDFIRST value is T then the system tries to derive it from other rules.

5. To derive a hypothesis from other rules, the system first gathers all the relevant rules which contain the hypothesis as the action part of the rule. The system then tries all rules to verify that hypothesis. If more than one rule succeeds to verify that hypothesis, then the certainty level is modified according to the combining scheme and is associated with the hypothesis in the fact list.
6. Step 4 and 5 are repeated recursively as many times as needed.
7. Finally the system reports one of the goal hypothesis is verified with an associated certainty level of the goal hypothesis. If the system fails to verify any of the goal hypotheses in the list, it assigns the default hypothesis as the previous epoch's hypothesis with the lowest certainty level.

The rule interpreter scheme at the highest level knowledge source is in the form of data-driven template

retaining scheme as is described before. The large number of patterns in a window makes it infeasible to apply a goal-driven backward reasoning scheme.

A scheduler performs the global control for the interaction of the discrete knowledge sources with the dynamic data sources in the blackboard. In fig. 4.4, the overall looping sequence of the scheduler is illustrated. The scheduler triggers the rule interpreter in a strict bottom-up fashion in the hierarchy of the knowledge base. At the beginning of a new speech processing, it triggers a procedure to set up the dynamic data base of the blackboard with various reference parameters. The sliding window is also updated by sliding one speech. Then it triggers the rule interpreter of the intermediate level template matching knowledge. The rule interpreter performs the reasoning in a backward chaining scheme to derive a conclusion with a set of rules and information on the same or other level of the dynamic data base of the blackboard. All the derived conclusions and intermediate results are stored in the dynamic data base. The derived final conclusion is stored in the sliding window for the next level processing. The scheduler triggers the contextual matching rules and search sequence scheduling rules. Finally, the scheduler triggers a procedure to attach the result of the speech processing to the report at the end of the speech processing.

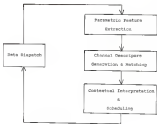


Fig. 4.3. The looping sequence of the Scheduler.

### Reasoning with Uncertainty

A well trained human expert possesses the capability of processing the record in a robust and efficient way. The human expert can easily score prominent speech which contains clear features of any sleep stage by perceiving the global patterns of the record. He, then, has the capability of interpreting ambiguous speech in the context of the record. This robust processing capability is especially important since the sleep EEG data include wide variations in standardization. The certainty factor model must be designed to reflect the above human expert's robust processing in interpreting ambiguous speech in a context of the record.

In the system, the lack of information in data and the uncertainties in related rules lead to a low confidence level in matching or even to a matching failure. Reduced information of an epoch, i.e., the matching result and its associated certainty level, is subject to the surrounding data context. Thus, the information within an epoch can be interpreted differently depending on the context. The role of the certainty level information is to provide a measure of matching closeness, which is then used in the next higher level contextual assignment.

The certainty factor model of the sleep EEG analyzing expert system includes the linguistic variables, i.e., High, Medium, and Low. These represent the certainty level of a

piece of knowledge and a corresponding weight value is associated with each variable as is shown in Fig. 4.9

Certainty Variable	Weight Value
High	+ 1
Medium	0
Low	- 1

Fig. 4.9. Certainty variables and associated weight values.

The certainty variables and their combination functions are defined based on the concept of weight belonging. A rule is stated with an associated certainty level in the action part based on the assumption that all the premise elements have a medium level of support. In other words, the certainty level of a rule premise is reduced under the assumption that each element of the rule premise is true with a medium level of certainty. The action part certainty level is modified during rule execution according to the combined certainty level of all the premise elements. A combined weight (CWF) value of a rule premise is defined as follows.

$$CWF = \frac{w_1}{n}$$

where  $QW_i$  the normalized combined weight  
 $W_i$  the weight value of the  $i$ -th condition in  
 the rule premise  
 $N$  total number of conditions in the rule  
 premise



Fig. 4-10. Certainty level combining scheme.

The combining scheme is illustrated in Fig. 4-10.

If more than one rule is executed, the certainty variable which has the highest certainty level is chosen for the action part of the rule. This scheme is reasonable because of the implied mutual exclusiveness of the templates. The following example illustrates the operational of the certainty factor scheme.

IF:    1) The alpha spindle activity is high, and  
        2) The delta wave activity is low, and  
        3) The wake wave activities are low  
 THEN:  The sleep stage of the speech is STAGE 2 with  
        a HIGH level of certainty.

The above rule implies that, the sleep stage of an speech would be scored as STAGE 2 with a high level of certainty under the assumption that all the conditions of the IF part of the rule are satisfied with a medium level of certainty. The certainty level for the speech will be modified according to the combining scheme with the actual certainty level of each condition in the rule premise. If the speech contains one alpha spindle, five seconds of alpha, and one second of delta, then the associated certainty levels for each condition in the rule premise are LOW, LOW, and HIGH, respectively.

$$DEF = (W1 + W2 + W3)/3 = (-1 + -1 + 1)/3 = -1/3$$

Thus, the certainty level of the rule action part is modified by decreasing the level by one; i.e., from high to Medium.

Explanation Mechanism

The data processing nature of the problem requires special consideration in the explanation mechanism design. The explanation mechanism can be accessed any time, during system execution and also after the system has finished the processing. The system stores all the rule identification codes of the executed rules in each speech in the order of the fired sequence. When an explanation is requested for a certain speech, the system displays all the parameters associated with the fired rules in the speech. The user, then, can trace the line of reasoning by selecting the parameters from the menu screen as is shown in appendix B. The system displays the explanation of how the system has derived the parameter, by displaying translated phrases with a list of the rules as is illustrated with an example in appendix A.

## CHAPTER 2 SYSTEM EVALUATION AND RESULTS

The complete system must be developed and tested with a large amount of data from a wide range of subjects by incrementally incorporating relevant rules into the system's knowledge base. The waveform recognition parameters, which are mostly based on the previous waveform parameters of the LANC system, were established by articulating the system with a wide range of subject records. A total of 112 rules are included in the token processing system's knowledge base, and these rules are listed in Appendix B. Presently, most of the classification rules are based on the Backus-Naur and Bates sleep staging criteria. In order not to lose the objectivity of the analysis, wide deviations from the Backus-Naur and Bates criteria are avoided as much as possible in this initial system evaluation. However, the developed system has the flexibility to allow modification and incorporation of more rules in the system through the knowledge-base editor. Potentially, there exists room for further performance improvement by elaborating on the system's knowledge base with a variety of contextual information.

The developed system is tested with a selected set of 25 records of subjects from 1 to 70 years old. The number

of subjects included in the present analysis is not sufficient to provide a thorough system performance validation. The validation is an involved process including processing of much more data from range of subjects. The system also requires a validation by professionals in sleep EEG research and its clinical application areas. Thus, the system development and validation require cooperation of the domain professionals as is generally true in other cases of expert system development.

However, from the results of the 14 records, a general perspective for problems can be illustrated with discussions on the nature of SCRODs, the system performance and its limitations, and ways of further improvements.

### Experimental Procedures

This study selects a total of 14 records of nocturnal subjects in three age groups. Group 1 contains seven records of six subjects between 5 to 28 years old. Group 2 contains five records of four subjects in the age range of 29 to 34 years old. Group 3 contains four records of four subjects from 47 to 55 years old. Entire night's EEG/EOG data have been recorded on a 1-track Langmuir 24 tape Recorder Model 1506 at 12/24 inch/sec. These data have been replayed at the same speed for processing. Three EEG channels, i.e., F7-P7, C3-A2, and C3-CAPs, and one EOG channel are

used in the analysis. The channel assignments for the waveform detectors are described in chapter II. The four channels are calibrated at the same level such that 50 ( $\mu$ v) EEG/EOG corresponds to 1.5 ( $\mu$ v) at the input to the early-processing system. A 50 Hz sinusoidal calibration signal is recorded at the beginning and end of each subject's EEG/EOG recording to indicate the 50 ( $\mu$ v) EEG level. Each channel signal is digitized at a 480 Ks sampling rate by a 12 bit A/D converter. All the channels are first lowpass filtered by a digital filter with a 3-dB cutoff frequency at 120 Hz. All the waveform detection parameters, except the delta amplitude threshold level, are kept the same as described in chapter II for all the subjects' records. Since the delta amplitude level is generally much higher for a young subject group, a different delta amplitude threshold, i.e., 77.2 ( $\mu$ v), is used for all the subjects of 13 years old and younger. The same threshold of 18.7 ( $\mu$ v) is used for all the rest of the higher age subjects. The token data of all subjects processed from the early-processing system are on-line acquired with a PDP-11/23+ system and stored on R102 disks. These data of 14 records constitute a data-bank which can also be used in the future for other types of token analysis purposes. The token data for one night generally occupies around 300 Kbytes. Minute-wise summarized token data files are sent to the Rainbow PC for the sleep stage scoring. The number of waveforms per channel

is counted for alpha spindles, K-complexes, and REM waves. The total wakefulness activity time per minute is counted for alpha spindles, beta spindles, delta waves, theta spindles, muscle artifact, and slow eye movements. If a wakefulness activity contains an interval of less than one second without the wakefulness, the interval is considered part of the wakefulness activity time in the minute.

### Protocol

The system performance is ultimately measured in terms of a man-machine agreement for the record scoring. The supplementary sleep staging manual of R.W. Jones, Jr., and M.B. Nash [1972] is used as a reference guide for the system's performance evaluation. The manual provides instructions for signal recording, scoring criteria, and training procedures for human scorers. They obtained a set of calibration records, which includes six normative subjects in the range of 27 to 34 years old, by an initial scoring with at least 90 % agreement between two experienced scorers and by final adjustments among the laboratory personnel. The set was used as the standard calibration records in that laboratory to test a human scorer's performance level. According to the manual, which is also true in most cases for other laboratories, a 90 % agreement rate with the standard calibration records is required for

the qualification of satisfactory scoring by a scorer. It is noticeable that the required agreement rate among experienced scorers is 80 %. Thus, it is the desired reference for an automated system's performance evaluation. Average agreements, across the six stages, of four trained human scorers with the six standard classification records are reported in the manual and are illustrated in Table 3.1.

The system's processing results are compared with the independent human scorer's results obtained from the sleep research laboratory of the Baylor College of Medicine, Houston, Texas. Table 3.2 shows a list of man-machine average agreement for the records. Overall average agreement of the 14 records is 82.4 %. The four records, 10319, 10114, 10087, and 10089, show especially poor agreement of far below 80 %. On the other hand, all the other 10 records are relatively evenly distributed between 82.4 and 94.2 %, as is illustrated in Fig. 3.1, giving a total average of 87.2 %. It is exemplified from the distribution of subject percentage agreement that the scoring agreement is quite subject dependent.

Table 3.3 shows the percentage agreement and the classification epochs' distribution across the sleep stages for the 14 records. The percentage agreement tables for each subject record are attached in appendix C. The overall epoch-by-epoch percentage agreement is 83.4 %, which is obtained by dividing the diagonal sum of the epochs by

Table 3.1. Percentages Agreement With The Standardized Scoring Across Six Calibration Records By Stage of Sleep. Add By Scorer (Ag72).

Sleep Stages	Scorer				Mean Across Scorers
	1	2	3	4	
0	88	83	86	88	86
1	78	83	80	79	80
2	88	88	84	88	88
3	82	28	88	70	69
4	88	91	88	90	88
5	94	93	93	93	93

Table 3-2. List of Average Agreement for each Record.

Group	Age	Records	Average Agt. for -                      stages 3 and 4 together	
			-	-
Group 1	5 - 18	10014 (15)	75.0	77.8
		10050 (18)	82.8	85.1
		10088 (23)	89.5	88.8
		10095 (23)	88.0	91.0
		10086 (23)	88.6	93.8
		10614 (23)	72.8	85.8
		11822 (28)	91.5	98.0
Group 2	18 - 34	12768 (25)	89.0	93.6
		12717 (27)	88.7	91.4
		12747 (29)	92.4	90.7
		12248 (34)	92.8	94.0
		12788 (34)	92.8	94.6
Group 3	45 - 70	10847 (48)	72.4	73.8
		11773 (52)	85.2	89.2
		10818 (58)	78.4	72.4
		11748 (70)	92.8	92.8
Total	-	-	83.4	87.0

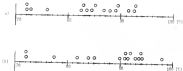


Fig. 8-1. Distribution of Percentage Run-Model Agreement for the 16 Records. a) with observation of stages 2 and 4, b) without observation of stages 2 and 4.

Table 5.3. Non-machine Agreement for the Total 18 Records (5 to 70 years old).

		Machine Score						(false negative)	
stage	stage	0	1	2	3	4	5	total age (%)	
0	0	484	38	4	0	1	7	484	98.1
1	1	38	117	87	0	0	12	184	40.4
2	2	44	27	3438	133	8	159	3658	89.8
3	3	0	1	49	192	22	4	323	85.4
4	4	0	1	19	190	484	8	788	83.8
5	5	78	49	133	7	0	1843	1895	87.1
total		611	227	3713	406	905	1878	7307	
age (%)		71.4	48.4	83.2	34.8	95.1	87.4		83.8
		98.1							87.5

\* no stages 3 and 4 discrimination

(false positive)

the total sum of the epochs in the table. Each stage-wise agreement should be considered in terms of both false positive and negative errors. The stage-wise percentage agreement shown at the right most column reflects the false negative error for each sleep stage, if the agreement rate is subtracted from 100 %. Similarly, the agreement rate of each stage shown at the bottom row of the table also reflects the false positive error, if the agreement rate is subtracted from 100 %.

Stage 2 scoring shows about 90 % agreement in both directions resulting in around 18 % of false negative and positive errors. However, there exists room for further improvement of Stage 2 scoring by allowing changes in the sleep episode detection parameters and filter structure mildly according to a subject's age group. Since, Stage 2 epochs occupy a significant portion of the total epochs, further increase in Stage 2 scoring will give a significant improvement in terms of total epochwise average agreement.

The REM stage (Stage 4) scoring shows also a relatively high agreement about 87 % in both directions resulting in less than 13 % of false negative and positive errors. Thus, the scoring of stages 2 and 4, which together occupy three fourths (3/4) of the total record, show relatively higher man-machine agreement than the scoring of the other stages. It is significant that the REM sleep stage becomes one of the most reliably scored stages. The

accuracy of REM stage scoring is relatively subject dependent upon the variations of REM characteristic. Most of the REM stage scoring errors result from the mis-scoring with Stage 1. For some subjects, REM waves appear abnormally together with edge spindles causing trouble in separating the REM sleep and Stage 1. In this study, this type error gives a decrease of 5.7 % in the total average agreement. The portion of 51.3 % of these errors results from the three poorly scored records, i.e., 40007, 10114, and 10719. If an REM channel is incorporated in the analysis, the REM sleep scoring can be improved further especially resulting in a better separation of REM sleep and wake. The REM detection algorithm sometimes gives a false positive REM detection during REM sleep requiring a further examination. However, this does not cause serious trouble since the false REM detections do not occur often, thus in most cases, the false REM detections can be easily overridden by the context information of other data or edge spindles. Thus, the Stage 1 scoring errors of the system are related more to the variations of subject REM characteristics than to the false positive REM wave detection.

The most significant error is the poor classification of Stage 1. The Stage 1 scoring shows a significant amount of both false positive and negative errors associated with the Stage 1. Stage 1 scoring also shows a significant amount of false positive error resulting from mis-scoring of

Stage 4 as Stage 3. The Stage 3 scoring errors associated with stages 2 and 4 contribute 8.7 % of error in the total average agreement, i.e., 494 mis-scored epochs among the total of 7887 epochs. Thus, it is noticeable that, without the Stage 3 error, the total average agreement is above 90 % for the system. However, the current scoring of Stage 3 is an inherently difficult problem, since the nature of Stage 3 is a type of transition between Stage 2 and Stage 4. More importantly, the human scorers also show a very low percentage agreement for the sleep stage 3 classification. This is illustrated in Table 2.2 which is obtained from the standard of Agnew and Webb. The four human scorers' average percentage agreement of Stage 3 classification with the six standard calibration records is only 40 %. It is important to point out that the inter-machine percentage agreement for the Stage 3 classification never becomes as high as the other stages regardless of the machine's high accuracy, because it is obtained from epoch-by-epoch comparison of the machine scoring with the relatively unreliable human scoring. It is, thus, very doubtful that the system can get a significant improvement in scoring Stage 3 by any other deliberate analysis of data sets. It seems more unrealistic to evaluate an automated system's performance by the present scheme of epoch-by-epoch comparison with the human scoring results. In an effort to improve sleep stage scoring accuracy, machine scoring is often reported without

separating the sleep stages 3 and 4. The overall percentage agreement of this system, without separation of the stages 3 and 4, is 87.3 %.

Stage 1 scoring shows a low agreement. This error is associated with the relatively low reliability of human scorer's Stage 1 classification. A Stage 1 epoch does not involve any sleep measures or activity, rather it is defined as a transient state between the other stages; therefore, it is susceptible to erroneous classifications into the adjacent epoch stages. Another reason for the low agreement of the Stage 1 scoring is that the Stage 1 scoring rules have not been articulated sufficiently in terms of contextual interpretation. Thus, the rules related to Stage 1 scoring need to be elaborated further by considering various contextual factors in the record. Moreover, since the total number of Stage 1 epochs is only about 3.8 % of the total epochs, the significance of Stage 1 error in the system performance is very small.

Stage 0 shows a high agreement rate of 90.1 % with a small false negative error ( $100 - 90.1 = 9.9$  %). On the other hand, Stage 0 shows a reduced agreement of 71.8 % with a false positive error of 28.2 %. This false positive classification error in the Stage 0 mostly results from the present system's scheme of handling arousal epochs. Arousal epochs are reported as Stage 0 instead of classifying the epochs into the surrounding epoch's stage as is the case in

human scoring. The separate arousal epoch reporting is desirable since the information on arousal is often important for clinical applications. By incorporating an RM channel in the analysis, a significant portion of Stage 3 error, specifically the misclassification of a REM epoch as Stage wake, can be reduced. If this portion of error is removed, the agreement of the Stage 3 scoring is also 88.1 % with a 13.7 % of false positive error. However, 88.3 % (88 from the total of 79 epochs) of this type error, i.e., misclassification of a REM epoch as a Stage wake, comes from a single record, 10889, which shows the lowest scoring agreement among the subjects. Thus, if this error from the record 10889 is not counted in the statistics, the false negative error of REM stage scoring is reduced to below 10 %, giving a 90.3 % average agreement.

The youngest age group records show the average agreement of 88.1 % as shown in Table 5-6. This age group shows 88.4 % of high agreement without separation of stages 3 and 4. The young adult age group records show the highest average agreement rate of 89.8 % as shown in Table 5-8. If stages 3 and 4 are not separated, then the agreement of this age group is 93.2 %. The oldest age group records reflect the lowest average agreement at 85.8 % as shown in Table 5-4. However, among the four subjects in this age group, two subjects' records, 10887, and 10888, belong to the previously described four records which display a large

Table 1.4. Hermachline Agreement for Group 1 (5 to 18 years old)

Machine Score (false negatives)

stage stage	0	1	2	3	4	5	total agr. (%)
0	180	13	3	0	1	1	197 81.6
1	20	43	34	0	0	3	110 87.3
2	7	27	1404	65	3	96	1492 88.6
3	0	1	97	116	20	4	148 49.0
4	0	0	11	180	300	8	592 88.7 <sup>a</sup>
5	1	28	71	7	0	791	898 87.8
total	218	132	1406	263	408	880	3407
agrch	87.1	87.7	81.6	82.5	94.6	87.8	86.1
				81.4			86.4

<sup>a</sup> no stages 3 and 4 discrimination

(false positive)

TABLE 3.8. Man-machine Agreement for Group 3 (28 to 34 years old).

Machine Score (false negative)

age age	0	1	2	3	4	5	total age, (5)	
0	87	3	1	0	0	0	91	80.5
1	7	28	8	0	0	0	33	43.5
2	7	3	4037	74	0	14	1134	91.4
3	0	0	34	84	11	0	129	68.1
4	0	1	0	30	48	0	79	80.3
5	4	4	12	0	0	603	613	94.3
total	75	38	1181	237	300	437	2179	
age(5)	84.8	48.8	83.3	75.4	81.0	94.0		84.7
				878.5				92.8

\* no ages 2 and 4 discrimination;

(false positive)

Table 5.6. Herzmachine Agreement for Group 3 (47 to 79 years old).

		Machine score						(false negative)	
age	group	0	1	2	3	4	5	total	age (%)
0		189	22	1	0	0	3	215	68.2
1		25	54	34	2	0	41	156	13.4
2		30	8	824	1	0	27	1002	90.4
3		0	0	14	12	0	0	26	65.2
4		0	0	0	0	0	0	0	-
5		74	13	20	0	0	588	675	71.3
total		318	77	879	13	0	671	1771	
age (%)		55.4	44.7	53.1	52.3	-	72.1		60.6

(false positive)

variability of EEG characteristics with fair amount of human scoring errors. Thus, it is not reasonable to represent the system's performance for this age group by the above agreement rate.

### Discussion

The disagreement between the automated sleep EEG scoring and human scoring is, as reviewed in the last section, is very much dependent upon the subject's EEG characteristics. However, the cause of error is compounded in its nature as a result of several erroneous features involved in the process. Among the major factors are: the early-processing system's detection accuracy, probable insufficiency of information extracted from the EEG/eye data, insufficient codification of sleep stage scoring rules, subject abnormality or wide variations in EEG characteristics, and human scoring errors and inconsistency involved in visual scoring. Unfortunately, straightforward solutions for the above listed problems are not readily available. Much of the problem is related to the human visual recognition process, which is not fully understood in several aspects in terms of application of machine intelligence and A.I. techniques. However, discussions on further improvements can be given based on the exposed limitations of the present methodology.

Presently, the EEG analyzing system is functionally divided in two independent parts, i.e., the early-processing system for waveform recognition and the taken processing system for sleep stage scoring. The serial communication link between the two is only for the sending of taken data from the early-processing system to the taken processing system. The waveform recognition parameters in the early-processing system are fixed. However, it is necessary to provide parameter adaptability as the system can automatically change values according to the information obtained from the higher level taken processing system or from other subject data. Thus, there can exist a kind of feedback loop such that the two separate parts can operate together constituting an incorporated single system. This idea is reasonable since most of the waveform activity parameters vary from subject to subject and even within a subject record. The human scorer has the capability to adapt his perception to detect the occurrence of waveforms in the record. The issue of keeping the waveform parameters constant to obtain an objectivity in the computer analysis is resolvable. The EEG analyzing problem is based on the detection of waveform occurrences in the record. The objectivity of computer analysis results from a consistent detection of each waveform occurrence without giving false positive or negative errors. The waveform parameters provided in various reports and standards must be regarded

as only marginal references for the definitions of waveforms. As long as the computer can detect the waveform consensus in a consistent way closely agreeing with a human scorer, it cannot be a question of whether the waveform parameters are kept constant or changed according to other related contexts. The objectivity in terms of waveform parameter values can be an issue for other aspects of computer analysis of EEG data, such as a study of individual waveform characteristics.

A self-adaptive mechanism is necessary to reflect a wider context of information during the data processing. Presently, a sliding window provides a partial solution to reflect local context information in the analysis. The contextual smoothing of the third layer processing, using the sliding window scheme, presently contributes a 1.8 % increase in the total average agreement of 83.4 %. Yet, a more flexible and powerful mechanism can adaptively modify system knowledge reflecting various context information in a wider record range. This is required to achieve a high agreement, since the human scorer has the capability to reflect the wide range of context information in the visual coding of the EEG data.

Sleep stage 3 scoring is the most serious task involved in the development of an automated scoring system. Unfortunately, the problem of low agreement of sleep stage 3 scoring cannot be solved readily, and it is not clear even

if it can be solved at all. The most typical example of inconsistency is assigning Delta data to stages by W.B. Webb [Webb]. He suggests the Delta amplitude threshold not be used, since without it basically the same amount of stage 3 and 4 sleep is observed in the old age group subjects giving a consistency among the various other age groups. If human scorers can not provide a consistent and reliable scoring for this stage, it seems more realistic to incorporate a human scorer's re-examination process of sleep stage 3 scoring with the computer analysis results during the system performance evaluation. The present scheme of blind speech-by-speech comparison is not suitable for performance evaluation of the system's stage 3 scoring.

## CHAPTER VI CONCLUSION

The new approach to automated sleep analysis, a knowledge-based expert system on top of a heuristic signal analysis technique, is applied to the development of an automated computer system for the multichannel EEG analysis. The new approach provides a different way of computer analysis of sleep EEG data based on the idea of simulating the human visual inspection process. The approach also provides a different user involving environment which achieves transparency in assessing the system's knowledge and displays system operation. These features are important in a domain like sleep EEG analysis.

The system is designed for intensive signal processing applications, where a great amount of data requires special considerations of processing efficiency and on-line processing and monitoring features. The rescheduling of the searching sequence, and the multichannel experts using a blackboard model and a sliding window scheme are considered in the design for the processing efficiency and the on-line monitoring application of the system. The waveform recognition system is designed and implemented in a digital environment including the detection for all waveforms such as REM, R-complexes, REM,

alpha, beta, delta, sigma, theta, muscle artifact, and ECG level. The knowledge-based token processing system, including the shell and the knowledge-base editor, is developed by employing sleep stage scoring rules simulating the human scorer's process of interpretation and classification of the sleep data.

The developed system is tested with a randomly selected set of 14 records of subjects from 4 to 70 years of age. The system shows an average man-machine agreement of 88.4 % for the records. The performance level of the present system is not considered as high as that of a human expert. However, the system's performance cannot be easily judged based on the agreement result with the selected records, since performance validation is an involved process including processing of much more data of a wide range of subjects. The system elaboration and validation also requires independence of the domain professionals in the process.

Potentially, there exists room for further improvement of performance by elaborating on the system's knowledge base with additional contextual information and also by further elaboration of waveform parameters. Presently, most of the classification rules are based on the Rechtschaffen and Kales sleep staging criteria. In order not to lose the objectivity of the analysis, wide deviations from the Rechtschaffen and Kales criteria, are avoided as

such as possible in the development of the system's knowledge base.

Besides the necessity of further rule refinements, there exist several potential limitations which can be addressed for further improvement of the system performance. The waveform parameters of the early-processing system have to be adjusted according to higher level context information obtained from the token processing system or from other subject data. This will significantly improve the early-processing system's detection reliability. Next, a self-adaptive learning mechanism is necessary to reflect wider contextual information during the data processing as discussed in chapter V. The sleep stage 3 scoring problem does not seem to have any feasible solution, although a good agreement of this stage scoring is significant in terms of total system performance. As discussed in chapter V, it is desirable to incorporate a human scorer's re-examination process of stage 3 scoring with the computer scoring results for the performance evaluation of an automated system, since human scorers do not provide a reliable and consistent sleep stage 3 scoring.

The sleep EEG analyzing problem provides an excellent example of a heuristic, knowledge-intensive problem domain for the application of an expert system approach. Objective EEG analysis and analytic problem solving models are not available, but the analysis relies on the visual inspection

and application of the heuristic interpretation rules of a well-trained human expert. In the heuristic domain like sleep EEG analysis, application of any analysis signal processing approach has significant limitations in designing an automated computer analyzing system, and an algorithm-based conventional programming approach is not appropriate to cope with the heuristic, potentially varying knowledge of the sleep EEG analysis. Expert system approach proposes a new way of solving the problem in this type of domain by providing a flexible way to codify human expert's heuristic knowledge and skilled process with an appropriate representation in the system.

However, there exist several fundamental limitations in realizing human-like intelligence in a computer by the current A.I. approaches which are mainly based on the description of features and rule-like inferences. The essential problems related with the incomplete commonsense knowledge and the lack of knowledge for some of human being's recognition processes, such as image-based inferences, similarity recognition, and relevance parsing processes are crucial barriers to overcome the limitation of current application-oriented A.I. technology in achieving a really competitive machine intelligence at a human expert's performance level. R.L. Gregory and M.R. Gregory address this issue and conclude that, with the current A.I. and expert system technologies, it is impossible to implement a

integrative intelligence is a computer with a human expert's level of performance [1985]. He articulates his arguments such that, the human expert's high level performance is ultimately related to his capability of handling a huge amount of special cases in different contexts, and this capability has been obtained through years of practice and experience. This then becomes a fundamental barrier in implementing the heuristic knowledge in a computer, since in most cases codification of the knowledge is inherently a difficult task and the amount of knowledge can easily exceed the manageable range of a computer. The core fundamental questions, i.e., whether or not the human scorer's deep EEG analyzing knowledge is sufficiently codifiable and whether or not the amount of knowledge to show human expert level performance is within the manageable range of a computer, are not yet answered. However, considering that presently no alternative ways of solving the problem of heuristic domains without using A.I. technology can be offered, it is realistic to accept the expert system approach and to expect its potential contributions in handling this type of heuristic problem by providing a way of incrementally codifying the expert knowledge.

The current study shows a new application of the A.I. and expert system approach to the EEG signal processing application domain. Although, this research focuses on the extracted sleep stage scoring, future research must

Incorporate other aspects of an expert system to provide an intelligent environmental tool in the sleep research and its clinical applications areas. All the extracted waveform activity information can be further manipulated by the computer in various ways according to the user's interests and can be provided for the user in a user-friendly intelligent manner. A natural language interface capability is important for a successful application of the expert system as an intelligent research tool for sleep research and related clinical applications. Since, significant information which can be further extracted from the stored waveform is not limited to any small number of fixed manipulations of the taken data, the system must interact with the user in a highly flexible way depending to the user's requirement of wide ranging information exploration. The system must incorporate all the taken processing knowledge which can extract potentially significant information from the waveform.

The approach and the techniques developed in this study can be further applied to other related signal processing applications domains like, signal processing and interpretation of other biological data, pulmonary disease diagnosis, patient monitoring and assessment, neurology, and other signal analysis and monitoring applications.

## APPENDIX A SYSTEM OPERATION EXAMPLE SCREENS

The system shows a top level selection menu at the beginning of the system operation. The top level menu is illustrated in Fig. A.1. A user can select one of the previously created knowledge bases or create a new knowledge base by user selection. If the user selects one of the previously developed knowledge bases, the knowledge base is read into the system from the disk. The next level menu is then displayed on the screen as is shown in Fig. A.2. If the user selects to create a new knowledge base, the system will interactively ask for values of the global variables. After the completion of the global data input, the system will lead to the next level menu for further editing of the knowledge base.

The menu shown in Fig. A.2 is the top level menu for a selected knowledge base. The user can run and test the knowledge base or, he can edit the knowledge base rules, parameters, variables, detector reliabilities, and query input parameters. The user can also simply list the knowledge base, and can save the modified or created knowledge base into a disk. The editing of the knowledge base is guided by user friendly menus and prompts. Examples

# **Figure 4.1: Top Level Menu for Knowledge Base Selection**

**ENTER A NUMBER FROM THE FOLLOWING MENU:**

1. ADD-KBASE
2. DEL-KBASE
3. CREATE A NEW KNOWLEDGE-BASE
4. EXIT

Fig. 4.1 Top Level Menu for Knowledge Base Selection

# **Figure 4.2: Sub Menu for Activity Selection**

**ENTER A NUMBER FROM THE FOLLOWING MENU:**

1. RUN
2. RULES
3. PARAMETERS
4. VARIABLES
5. DETECTOR-IN-QUERY-Phase
6. BACK
7. QUIT

Fig. 4.2 Sub Menu for Activity Selection

of screens for rule editing sessions are shown in Figures A.3, A.4, A.5, and A.6.

At the beginning of the execution, the system asks several questions for user inputs such as subject's age, record number, and date. Then the system displays all the query input parameters one by one with a default value as is illustrated in Fig. A.7. If the user wants to change the value of the query parameter, he can input a new value with an associated certainty level. The system then starts running and displays speech-wise classification results on the screen. An example of monitoring screen, while the system is running, is illustrated in Fig. A.8. Rule identification codes for all the related rules in each speech classification are also displayed together with the classification result. The left most column displays the final score for each speech. A running window containing the date of the current five speeches, is also shown at the bottom of the screen. Contextual manipulations are performed at the end of every speech classification when new speech data is attached to the window making all the date slide one speech position. The first speech in the running window becomes the final classification result. This is listed together with the speech-wise classification rules executed before context sliding.

During the execution, a user can interrupt at any time. If he wants an explanation of the results, by pressing

```

Report System Shell is BRO-CRASH
TOPPING Rules
RULE-GROUP CHANNEL-GRP
Edit CHANNEL-GRP rules. Modify

```

```

Enter a Number from the following menu:
1. INSERT-RULE
2. DELETE-RULE
3. MODIFY-RULE
4. LIST-RULE
5. QUIT

```

Fig. A.3. Menu for Rule Edition

```

Report System Shell is BRO-CRASH
TOPPING Rules
RULE-GROUP CHANNEL-GRP
Edit CHANNEL-GRP rules. Modify
*** Insert rule-3 at ALPHA-08 ***
Rule 1 of 2

```

```

Number is an atom code or 0 for rule.

```

Fig. A.4. An Sample Screen for Rule Insertion.

```

***** Report System Status *****
TOPEND, rules
RULE-GROUP: CHANNELS-GRP
END CHANNELS-GRP rules - modify
*** Insert Rule-6 of ALPHA-ON ***
Rule 1.0 : A-00
Enter Premise:
(Rule pass val) or (Rule pass val)

```

Fig. 8.3. Rule Premise Insertion

```

***** Report System Status *****
TOPEND, rules
RULE-GROUP: CHANNELS-GRP
END CHANNELS-GRP rules - Modify
*** Insert Rule-6 of ALPHA-ON ***
Rule 1.0 : A-00
Enter Premise: (OT ALPHA-TIME 0)
Enter Action:
(Rule6 assert) (pass val OT) or (Rule6 val OT)
(Rule6 High 000)

```

Fig. 8.4. System's Guidance Example During Rule Editing

```

***** Report: System Output: 101-1010-00000 *****
Date: 11-18-1988
Subject Number: 11717
Subject Age: 27
*** Query Parameters ***

-10- Use Following Selected Values On Run: 101-1010-00000-
(FCB-ALPHA CODE W)

```

Fig. 4.3 Query Parameter Values Input

```

***** Expert System Shell (to end again) *****
Date: 11-13-1987
Subject Number: 11717
Subject Age: 27
*** Query Parameters ***
CMR-ALPHA High 80
CMR-DELT High 80
*** Running Sleep Stage Scoring ***

***** Enter 0 to quit ***** Press F to pause or S to stop counting

1 : CB-2 80 CB-2 80 (0-12 0-24 A-2 0-16 0-32 0-64)
2 : CB-2 80 CB-2 80 (0-12 0-24 A-2 0-8)
3 : CB-2 80 CB-2 80 (0-12 0-24 A-1 0-8)
4 : CB-2 80 CB-2 80 (0-12 0-32 A-2 0-16 0-32 0-24 0-32 0-17 0-24)
5 : CB-2 80 CB-2 80 (0-12 0-32 A-1 0-8 0-24 0-32 0-17 0-24)

CB-2 0-0 0-0 0-0 0-0 0-0
0 0 0 0 0 0
CB-2 0-1 0-2 0-3 0-4 0-5 0-6

50 : CB-2 80 (0-12 0-24 0-11 0-15 0-2 0-8 0-8 0-32 0-41 0-16)

```

Fig. A-8. Monitoring Screen During System Run.

the 'P' key. The system provides an explanation mechanism such that the user can trace a rule execution line. User can trace the line of reasoning by selecting all the related parameters listed as is shown in Fig. A.8 for an example. An example of explanation is shown in Fig. A.10.

```

Report System Shell To SAS-SASL
Date: (12-12-1983)
Subject Number: 11757
Subject Age: 30
Sex: Male
*** Running Sleep Stage Scoring ***

***** Below are the following items *****
1. STAGE      2. WAKE-WAKE  3. DELTA      4. REM      5. MINUTE
6. WLF-WAKE  7. ALPHA     8. ALPHA-TIME  9. DELTA-TIME 10. SLEEP
11. ALPHA-COUNT 12. REM-COUNT 13. Q13

```

Fig. A 8. Parameter Selection Menu for Explanations.

```

Report System Shell To SAS-SASL
Date: (12-12-1983)
Subject Number: 11757
Subject Age: 30
Sex: Male
*** Running Sleep Stage Scoring ***

```

```

***** Below are the following items *****
*** Explanation minute : 1 ***

```

```

Rule ID : 6-12
IF : (EE WAKE-WAKE STAGE)
THEN : (STAGE STAGED W)

```

Sleep stage of the epoch is determined as STAGED by the above rule 6-12 such that if an epoch's wake related wave scoring is high, then the epoch is scored as STAGED with a medium level of certainty.

Fig. A 10. An Example of Explanation.

## APPENDIX B SYSTEM RULES

The current system contains 111 domain rules in the knowledge base of the system. The system can be further enhanced by adding more rules. In this appendix, the rule base of the current system is listed in a summarized table form.

Each waveform activity time or number of occurrences per minute is associated with the reliability factor of this waveform detection, and these data constitute a part of the bottom level data plane. Each wave activity of the epoch is then described as High, Medium, and Low according to the level of occurrence in each epoch. The waveform activity description is associated with a certainty level, either High, Medium, or Low, which is obtained by fuzzyfication rules within the range of each activity level and also by taking into account the associated waveform detector reliability level. A set of fuzzyfication schemes employed in the system is shown in Table B-1 for each wave activity.

New wave-activities can be further defined by combining the above described information. These new descriptors can give further abstraction of the waveform activity data. This system includes the descriptors of Wake-F-Activity and Sleep-W-Activity. The Wake-W-Activity

Table B.3. Fertilization Scheme Table.

Activity by Level	High			Medium		Low		
	H	H	L	H	L	H	H	L
Acidic	135	130	115	15 3 = 3 10	-	110	15	
Base	130	115	100	10 3 = 3 3	-	10	-	
Saline	130	-	120	30 3 = 3 15	-	120	15	
Algae	10	5	-	1	-	5	-	
Phyto	120	115	110	10 3 = 3 5	-	15	-	
Mycelia	130	120	-	20 3 = 3 5	-	-	-	10
SSB	-	125	-	15 3 = 3 5	-	15	-	
SSB	10	5	-	1	-	5	-	
Fluorop	10	5	-	1	-	5	-	

reflects the level of the sleep activities which are closely related with subject's wake state, i.e., combined information of alpha-activity and muscle-activity. The Sleep-W-Activity is obtained by combining the wake-activity information of alpha spindle and K-complexes. The definition rules for the Wake-W-Activity and the Sleep-W-Activity are shown in Table 2.2 and 2.3, respectively.

Each epoch is then classified into one of the stages according to the classification rules. The classification rules provide templates for each stage. The templates are obtained by the combination of the wake-activity descriptors. Each epoch is matched with one of the templates in the classification rules and those epochs which fail to match are classified on the previous epoch's stage with the lowest certainty level. Continuous manipulation will be performed on the intermediate classifications results at the next level processing. The classification rules for each stage include the Rechtschaffen and Kales classification standards. Key features of each stage are described in the following and summarized in Table 2.4.

**Stage 0:** Stage 0 templates are obtained by the appearance information of muscle artifact, alpha activity, and/or eye movement activity. The other sleep activities, such as alpha spindle, K-complexes, and delta activities are used as the exclusive information for Stage 0 templates. This level is

Table B.2: Combination Rules for Wake-Up-Activity.

	High			Medium		Low	
	H	M	L	H	L	M	
Alpha-Activity	H	M	M	M	M	L	
Beta-Activity	M	M	M	L	L	M	

Table B.3: Combination Rules for Sleep-Activity.

	High			Medium		Low	
	H	M	L	M	L	H	M
Sleep-Activity	-	M	-	M	L	-	L
Awake-Activity	-	-	-	-	M	-	M

Table B.4. Classification Templates.

Activity descriptor	Stage 0		Stage 1		Stage 2		
	H	L	H	L	H	H	L
Wake-sleep	H	H	<u>H</u>	L	L	L	<u>H</u>
Sleep-sleep		L	L	L	H	H	
Alpha							
Beta						<u>H</u>	
Delta	L	L	L	L	L	L	L
Sigma							
Theta							
Paradox							
REM							
REM		<u>L</u>	L	L		L	L
Sleep			L				
WAKE	<u>L</u>		<u>L</u>				
Delta-sleep							<u>H</u>
Subject-Alpha							
Under-drag							
Pre-1			<u>L</u>		<u>L</u>	<u>H</u>	<u>L</u>
Pre-2			<u>L</u>				

Note: Underlines indicates the location of the element.

Table B.4--continued

Activity Description	Stage 3	Stage 4	Stage 5			
	L	H	H	H	L	L
Index-move	L	L	L	L	L	L
King-move			L	L	L	L
Alpha						
Beta				H		
Delta	H	H	L	L	L	L
Epsilon						
Theta						
Nucleus						
SEP						
SEP			L			
Scrap						
SCUTE			H	H		
Two-to-three						
Subject-Alpha						
Under-drag						
Year 1					H-3	
Year 2						H-3

Note: Underlines indicates the negation of the element.

high for the Stage 0 epochs and this EEG information gives a clear separation between Stage 0 and REM sleep (Stage 5). Since the REM channel is not utilized in the system, the level of alpha activity (for a high alpha subject) and muscle artifact provide the separation of REM sleep from Stage 0 in addition to the REM activity information.

Stage 1: Stage 1 templates are mostly based on the absence of wave activities such as Wake-W-Activity, Sleep-W-Activity, delta activity, and REM activity, and occurrence of beta activities.

Stage 2: The appearances of alpha spindles and K-complexes provide the clearest and most reliable templates for Stage 2. Since the alpha spindles and K-complexes also appear in Stage 3 and Stage 4, the delta activity level is used to determine the separation of Stage 2 from stages 3 and 4.

Stage 3, 4: The level of delta activity provides the templates for the stages 3 and 4.

Stage 5: The REM, the beta activity, and the disappearance of the other wave activities, contribute the major part of Stage 5 templates. If the REM is utilized in the system, the low

RMF amplitude information can provide a supplementary condition for the Stage 3.

The contextual smoothing with a running window plays an important role in simulating the human speaker's visual inspection of the record. The contextual manipulation is performed with the running window of five consecutive epochs. Abstracted high level information, i.e., a classification stage and a matching certainty level of each epoch, provides the context data for the window. The major contextual manipulation rules are briefly described in the following and are summarized in Table 8.1.

- a The Stage 1 epochs which precede within five epochs from the RM stage are all smoothed into Stage 3.
- a Stage 1 epochs which succeed RM epochs are all smoothed into Stage 3.
- a Stage 1 epochs are smoothed into the surrounding epoch's stage, if the Stage 1 epochs are not associated with the highest certainty level and appear in less than three consecutive epochs.
- a Stage 2 epoch which is surrounded by the RM epochs is smoothed into Stage 3, if the matching level of Stage 2 is not high.
- a If Stage 3, 2, 1 epochs, which are associated with the lowest matching certainty level, are surrounded by the other stage epochs which are

Table B.3. Contextual Smoothing Rules.

$$\begin{aligned} & \text{---> } (a-0 \neq a-0 \neq a-1 \neq a-2 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-2 \neq a-0 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-0 \neq a-2 \neq a-0 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-2 \neq a-0 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-0 \neq a-1 \neq a-0 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-2 \neq a-0 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-1 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-2 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-2 \neq a-1 \neq a-2 \neq a-0 \neq) \\ & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \\ & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-2 \neq a-2 \neq a-0 \neq a-2 \neq a-2 \neq) \\ & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \\ & \text{---> } (a-2 \neq a-2 \neq a-2 \neq a-2 \neq a-2 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-1 \neq a-0 \neq a-0 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-0 \neq a-0 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-2 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq) \end{aligned}$$

$$\begin{aligned} & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-0 \neq a-0 \neq) \\ & \text{---> } (a-0 \neq a-0 \neq a-0 \neq a-0 \neq a-0 \neq) \end{aligned}$$

NOTES: The symbol  $\neq$  indicates any equality level.

Table 8 (Continued)

	$\begin{pmatrix} a-1 & * & a-2 & * & a-3 & * \\ a-3 & 1 & a-3 & * & a-3 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & * & a-2 & 1 & a-3 & 1 & a-2 & * & a-3 & * \\ a-2 & * & a-2 & 1 & a-2 & 1 & a-2 & * & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & * & a-3 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & 1 & a-3 & * & a-2 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & 1 & a-2 & * & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-4 & * & a-4 & * & a-3 & * & a-4 & * & a-4 & * \\ a-4 & * & a-4 & * & a-4 & 1 & a-4 & * & a-4 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-4 & 1 & a-3 & * & a-2 & * & a-4 & * & a-4 & * \\ a-4 & * & a-4 & 1 & a-4 & 1 & a-4 & * & a-4 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-3 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & * & a-2 & * & a-3 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & 1 & a-2 & * & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-4 & * & a-2 & * & a-2 & * & a-3 & * & a-3 & * \\ a-4 & * & a-3 & 1 & a-3 & 1 & a-3 & * & a-3 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-3 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & * & a-2 & * & a-1 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & 1 & a-2 & * & a-2 & * \end{pmatrix}$
$\rightarrow$	$\begin{pmatrix} a-2 & * & a-2 & * & a-1 & * & a-2 & * & a-2 & * \\ a-2 & * & a-2 & 1 & a-2 & 1 & a-2 & * & a-2 & * \end{pmatrix}$

Note: The symbol \* indicates any certainty level.





associated with a high matching certainty level, and the length of the intervening spaces are less than three, then the intervening spaces are smoothed into the surrounding speech's stage.

Scheduling of the searching path is performed by the arrangement of the goal hypotheses of the intermediate level classification rules. The system can employ any number of scheduling rules which can assign each searching path by matching against the running status. However, for simplicity, the current scheme employs only six rules and the searching paths are empirically decided as the following depending on the last speech's stage of the window.

Search Path	Last speech's Stage
{a-0 a-1 a-2 a-3 a-4 a-5}	stage 0,
{a-1 a-2 a-3 a-4 a-5 a-6}	stage 1,
{a-2 a-3 a-4 a-5 a-6 a-7}	stage 2,
{a-3 a-4 a-5 a-6 a-7 a-8}	stage 3,
{a-4 a-5 a-6 a-7 a-8 a-9}	stage 4,
{a-5 a-6 a-7 a-8 a-9 a-10}	stage 5,

APPENDIX C  
MAN-MACHINE SCORING AGREEMENT TABLES  
FOR EACH SUBJECT RECORD

Table C.1. Man-machine Agreement Table for 18718 (5 years old)

		Machine Score						(false negative)	
stage	stage	0	1	2	3	4	5	total	agr. (%)
0	0	37	3	1	0	0	0	40	92.3
1	0	0	9	0	0	0	0	9	100.0
2	0	0	0	100	20	0	0	120	83.3
3	0	0	0	0	10	7	0	17	58.8
4	0	0	0	0	0	100	0	100	100.0
5	0	0	10	20	0	0	107	137	73.7
<hr/>									
total	0	39	30	101	40	107	107	424	
agr (%)	94.9	91.3	89.1	11.7	83.8	71.7		74.0	
									79.8

\* no stages 2 and 4 discrimination.

(false positive)

Table C.2.      Non-machine Agreement Table for 1950 (5 years old)

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total	agr (%)
stage								
0	13	0	0	0	0	0	13	300.0
1	7	4	5	6	0	0	26	25.0
2	1	3	207	21	0	1	233	92.8
3	0	0	0	21	1	0	22	98.8
4	0	0	0	42	54	0	96	100.0
5	1	7	22	1	0	122	153	94.8
total	24	14	225	61	55	121	596	
agr (%)	48.5	28.8	92.0	86.5	98.8	99.2		83.5
				*98.0				*99.1

\* no stages 3 and 4 discrimination.

(false positive)

Table C-5. Map-Machine Agreement Table for 2018 (2 years old).

stage	Machine Score						(Cases negative)	
	0	1	2	3	4	5	total	agt. (%)
0	58	0	0	0	1	0	59	98.3
1	3	0	8	0	0	0	9	0.0
2	1	0	265	12	0	0	278	99.3
3	0	0	2	24	1	0	27	88.9
4	0	0	0	1	63	0	64	99.2 <sup>a</sup>
5	0	0	14	0	0	48	62	70.2
TOTAL	62	0	287	37	64	48	538	
agt. (%)	93.3	0	98.3	94.6	97.8	100.0		92.5
*97.8							98.3	

<sup>a</sup> no stages 3 and 4 discrimination

(false positive)

Table 0-4. Man-machine Agreement Table for 18109 (13 years old).

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total	agr.(%)
stage								
0	5	1	0	0	0	0	6	83.3
1	2	3	8	0	0	0	13	33.3
2	1	10	230	1	0	3	246	94.3
3	0	0	6	8	1	0	15	83.3
4	0	0	2	17	32	2	53	83.3 <sup>a</sup>
5	0	2	1	0	0	126	129	97.8
total	8	14	247	26	33	136	484	
agr.(%)	83.3	33.3	93.1	95.8	97.0	97.1		88.0
								180-0

<sup>a</sup> no stages 2 and 4 discrimination.

(false positive)

Table C.5. Misclassification Agreement Table for 10000 (10 years old).

Positive Score							(false negative)	
stage	0	1	2	3	4	5	total agr.(%)	
stage								
0	18	2	0	0	0	0	18	93.0
1	1	13	3	0	0	0	15	88.0
2	1	0	190	3	0	3	197	98.4
3	0	0	17	29	0	0	46	93.0
4	0	0	0	47	48	0	95	92.0 <sup>a</sup>
5	0	1	1	0	0	118	120	98.0
total	18	15	200	79	48	121	581	
agr(%)	93.0	83.3	99.5	96.7	100.0	97.5		94.4
				93.0				93.8

<sup>a</sup> no stages 3 and 4 discrimination.

(false positive)

Table C.6. Man-machine Agreement Table for 2012 (12 years old)

stage	Machine Score						(false negative)	
	0	1	2	3	4	5	total	avg. (%)
0	8	8	1	0	0	1	18	66.7
1	3	30	3	0	0	3	39	76.8
2	1	8	177	0	0	58	236	62.8
3	0	1	10	0	0	4	15	0.0
4	0	0	8	48	8	3	67	32.1 <sup>a</sup>
5	0	3	8	0	0	137	148	64.5
total	12	47	205	48	8	182	502	
avg (%)	66.7	63.8	67.8	0.0	100.0	76.9		72.8
				7180.8				768.8

<sup>a</sup> no stages 2 and 4 discrimination.

(false positive)



Table C.3.      Non-machine Agreement Table for 1978 (25 years old).

		Machine Score						(false negative)	
stage		0	1	2	3	4	5	total agr.(%)	
stage									
0	9	3	1	0	0	0	3	16	69.2
1	1	4	4	0	0	0	2	11	36.4
2	0	0	218	18	0	0	0	236	92.4
3	0	0	0	22	1	0	0	23	99.7
4	0	0	0	21	10	0	0	31	100.0
5	0	1	0	0	0	0	188	189	99.4
total	10	8	224	41	11	120	471		
agr.(%)	92.0	88.7	97.8	99.1	99.8	97.5		99.2	
								*75.8	*92.8

\* no stages 3 and 4 dissociation

(false positive)

Table 6.8. Man-machine Agreement Table for 11717 (27 years old).

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total	agr.(%)
stage	0	1	2	3	4	5		
0	13	0	0	0	0	0	13	100.0
1	0	8	3	0	0	0	8	75.0
2	0	0	204	1	0	0	204	95.3
3	0	0	11	7	3	0	20	33.0
4	0	1	8	18	20	0	47	42.8 <sup>*</sup>
5	0	0	4	0	0	218	218	96.8
total	13	7	226	28	23	218	431	
agr(4)/100.0	88.7	85.1	94.8	92.8	91.7		86.7	
				99.6				99.4

\* for stages 3 and 4 discrimination.

(false positive)

Table C.32. Hammett Agreement Table for 1242 (29 years old).

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total agr.(%)	
stage								
0	13	0	0	0	0	0	13	100.0
1	1	3	2	0	0	0	6	58.0
2	3	1	304	1	0	1	310	94.1
3	0	0	21	8	0	0	29	33.1
4	0	0	0	37	14	0	51	27.8 <sup>a</sup>
5	1	0	0	0	0	127	128	93.4
total	18	4	335	46	14	138	643	
agr.(%)	61.1	75.0	88.8	33.3	100.0	98.2		82.4
								888.7

<sup>a</sup> for stages 3 and 4 discrimination.

(false positive)

Table C.11. Run-machine Agreement Index for sides (24 years old).

Machine Score							(Index negative)	
stage	0	1	2	3	4	5	total	agr (%)
0	30	0	0	0	0	0	30	100.0
1	4	5	0	0	0	3	12	41.7
2	1	1	100	40	0	3	145	60.8
3	0	0	0	30	5	0	35	85.7
4	0	0	0	0	0	0	0	*100.0
5	3	1	10	0	0	100	114	67.6
total	38	7	210	70	5	108	438	
agr (%)	73.4	71.4	68.1	61.1	0.0	95.2		82.8
				*68.0				*61.0

\* no stages 3 and 4 discrimination.

(Index positive)



Table C.12. Regression Agreement Table for LOGST (43 years old).

Machine Score							[false negative]	
stage	0	1	2	3	4	5	total age (%)	
stage	0	1	2	3	4	5	total age (%)	
0	43	8	0	0	0	1	71	87.3
1	3	9	13	0	0	93	55	13.8
2	0	3	148	1	0	43	175	78.9
3	0	0	0	13	0	0	13	100.0
4	0	0	0	0	0	0	0	-
5	3	4	15	0	0	100	122	82.6
total	70	38	176	13	0	175	457	
age (%)	88.4	34.3	85.3	93.3	-	87.1		73.4

[false positive]

Table C.14. Haystacking Agreement table for 11771 (28 years old).

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total	agr.(%)
stage	0	1	2	3	4	5		
0	5	11	1	0	0	0	17	89.4
1	2	9	13	0	0	7	31	100.0
2	4	3	338	0	0	12	357	94.9
3	0	0	14	0	0	0	14	0.0
4	0	0	0	0	0	0	0	-
5	0	0	0	0	0	58	58	100.0
total	12	23	358	0	0	77	470	
agr.(%)	41.7	80.0	91.7	-	-	78.0		83.2

(false positive)

Table C.12. Sub-machine Agreement Table for 1989 (52 years old).

Machine Error							(Index negative)	
0	1	2	3	4	5	total	age (1)	
0	20	1	0	0	0	21	97.0	
1	11	0	0	0	0	11	10.0	
2	20	0	140	0	0	160	99.7	
3	0	0	0	0	0	0	-	
4	0	0	0	0	0	0	-	
5	40	0	0	0	0	40	92.8	
total	111	1	140	0	0	252	97.0	
age(1)	10.0	0.0	99.7	-	-	99.4	71.4	

(Index positive)

Table C.18. Rep-ranking Agreement Table for 11740 (70 years old)

Machine Score							(false negative)	
stage	0	1	2	3	4	5	total	apr(15)
stage								
0	100	1	0	0	0	0	100	95.0
1	7	14	4	0	0	0	27	58.5
2	0	0	105	0	0	2	107	96.8
3	0	0	0	0	0	0	0	-
4	0	0	0	0	0	0	0	-
5	0	4	1	0	0	55	60	85.7
Total	118	24	110	0	0	57	309	
apr(15)	86.4	66.7	97.3	-	-	96.5		93.8

(false positive)

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